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Testing average traffic fatality using sampling plan for exponentiated half logistic distribution under indeterminacy

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ABSTRACT

A time-truncated sampling plan for the exponentiated half logistic distribution under the indeterminacy is developed in the present investigation. The proposed design parameters are ascertained by fixing the indeterminacy parameter with the known shape parameter. For different values of indeterminacy parameters at known shape values, the parameters of the proposed plan are determined. The results show that the indeterminacy parameter influences the sample size of the proposed design for exponentiated half-logistic distribution. The results clearly indicate that while indeterminacy parameters increase, the sample size reduces. The relevance of the designed plan is established using data set on traffic fatality on roads in the United States. From the traffic fatality illustration, it is resolved that the proposed plan is helpful to test the aggregate traffic fatality at more modest values of sample size as analogized to the available classical sampling plan.

Introduction

Taffic fatality is an essential constraint of national highway management. The highway authorities' are paying attention to estimate the average traffic fatality for the subsequent day, after that month, or perhaps after that year, see [16,35,36] for more elaborate. In this situation, the highway authorities' are attracted to examine the hypothesis of average traffic fatality is same as prescribed average traffic fatality verses the rival hypothesis of the average traffic fatality contradicts considerably. When testing the hypothesis, in real situation it is difficult to note down the average traffic fatality in a year. At this juncture a few representative days called as samples and hence the corresponding average traffic fatality could register for those representative days or locations. Stated hypothesis could rejected when average traffic fatality, called as acceptance number of days or location, is greater than or same as prescribed average traffic fatality for a specified number of days or locations. Since the conclusion of average traffic fatality is carried on the available data, there are two possible wrong decisions namely type-I error and type-II error respectively. The acceptance sampling plan would assist highway authorities' to select representative days or locations and acceptance number of days or locations which optimizes both

Abbreviations: SSP, Single sampling plan; EHLD, Exponentiated half logistic distribution; NEHLD, Neutrosophic exponentiated half logistic distribution; npdf, neutrosophic probability density function; NRV, neutrosophic random variable; pdf, Probability density function; ncdf, neutrosophic cumulative distribution function; OC, Operating characteristic; NHTSA, National Highway Traffic Safety Administration.

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type-I and type-II errors simultaneously. The fine points regarding the acceptance sampling plans are available in [33] and [34].

The traffic fatality data is registered arbitrary from total situations and it has comes from some distribution according to distributional theory. Exponentiated half logistic distribution is a good model amongst the other distributions to apply for forecasting and estimating the traffic fatality. To predict and measure the parameters of distributions under traditional statistics could be employed if all the values and quantities are determined. Whereas in real world applications like traffic fatality observations are generally registered in an intervals. In this situation, traditional methods and classical distributions could not suitable to apply the traditional statistical distributions based on classical statistics. Whereas the statistical methods based on fuzzy logic could be employed for computing endeavors. Jamkhaneh et al. [14] developed the single sampling plan (SSP) based on fuzzy environment. Jamkhaneh et al. [15] studied the consequence of sampling error for examination based on fuzzy environment. [27] developed a SSP based on fuzzy logic. Some more works on SSP based on fuzzy logic approach include in [3,31] and [32].

In a real world applications like measure of determinacy or indeterminacy or falseness information available in the neutrosophic logic for more details are available in [28]. He argued that combine classical statistics with a fuzzy setting, do not offer background information on the measure of indeterminacy. The methods developed under neutrosophic statistics have more acceptability in different fields due to its generalized nature. The neutrosophic logic provides details regarding the measures of determinacy, indeterminacy, and falseness, see [28]. Hence, the more generalization of fuzzy logic methods and interval-based study is the neutrosophic logic techniques. Resent years more researchers concentrated on neutrosophic logic methods to address diversified real world issues and proved that it is effective than fuzzy logic approach for more details can be seen in Smarandache and Khalid [2,18,19,20,30] and [21]. The neutrosophic statistics technique is an inspiration from neutrosophic logic methods, more details are available in [29] and [8,12] pointed out that “The neutrosophic statistics gives information about the measure of determinacy and measure of indeterminacy. The neutrosophic statistics reduces to classical statistics if no information is recorded about the measure of indeterminacy”. Some more latest studies on acceptance sampling plans based on this area can be seen in [1,4,6,7,22] and [5,10,11] studied various sampling plans for the Weibull distribution and [9] introduced indeterminacy in sampling plans technology based on Weibull distribution to testing average wind speed. More recently [17] considered for monitoring COVID-19 cases under uncertainty and [23] studied various sampling inspection plans for cancer patients using gamma distribution under indeterminacy. In this paper we are adopting the same methodology to develop the SSP for exponentiated half logistic distribution (EHLD) under indeterminacy.

Accessible here and now the SSP based on traditional statistics technique and fuzzy logic methods do not provide knowledge on quantifying of indeterminacy. Through revisiting the various publications, we came to know that no attempt was taken place on time-truncated acceptance sampling plans for the neutrosophic exponentiated half logistic distribution (NEHLD). The attempt in this piece of material is on the NEHLD and useful for examine the average traffic fatality. The plan constants for examine the hypothesis will be obtained on optimize the both type-I and type-II errors simultaneously. It is anticipated that a smaller sample size is needed for examine the average traffic fatality using the developed SSP.

Methodologies

The aim of this section is an introduction on the EHLD based on neutrosophic statistics. In this section we will also demonstrate the blueprint of the SSP to investigation the average traffic fatality based on indeterminate situation.

Exponentiated half logistic distribution

We will provide a brief summary about the EHLD. The EHLD was acquainted and contemplated quite comprehensively by [13], further [24–26] studied for various acceptance sampling plans for this distribution. Suppose that $f(t_N) = f(t_L) + f(t_U)I_N; I_N\epsilon[I_L, I_U]$ be a neutrosophic probability density function (npdf) with determinate part $f(t_L)$, indeterminate part $f(t_U)I_N$ and indeterminacy period $I_N\epsilon[I_L, I_U]$. Note that $t_N\epsilon[t_L, t_U]$ be a neutrosophic random variable (NRV) follows the npdf. The npdf is the generalization of pdf under classical statistics. The proposed neutrosophic form of $f(t_N)\epsilon[f(t_L), f(t_U)]$ reduces to pdf under classical statistics when I_L=0. Based on this information, the npdf of the EHLD is defined as follows

$$f(t_N) = \left\{\left(\frac{2\theta}{\sigma}\right)\frac{\left(1-e^{-\frac{t_N}{\sigma}}\right)^{\theta-1}}{\left(1+e^{-\frac{t_N}{\sigma}}\right)^{\theta+1}}\right\} + \left\{\left(\frac{2\theta}{\sigma}\right)\frac{\left(1-e^{-\frac{t_N}{\sigma}}\right)^{\theta-1}}{\left(1+e^{-\frac{t_N}{\sigma}}\right)^{\theta+1}}\right\}I_N;\, I_N\epsilon[I_L, I_U] \tag{1}$$

where σ and θ are scale and shape parameters, respectively. It is significant to note that the developed npdf of the EHLD be the oversimplification of pdf of the EHLD based on classical statistics. The neutrosophic form of the npdf of the EHLD reduces to the EHLD when I_L=0. The neutrosophic cumulative distribution function (ncdf) of the EHLD is given by

$$F(x_N) = \left\{\left(\frac{1-e^{-\frac{t_N}{\sigma}}}{1+e^{-\frac{t_N}{\sigma}}}\right)^{\theta}\right\} + \left\{\left(\frac{1-e^{-\frac{t_N}{\sigma}}}{1+e^{-\frac{t_N}{\sigma}}}\right)^{\theta}\right\}I_N;\quad I_N\epsilon[I_L, I_U] \tag{2}$$

The average lifetime of the NEHLD is given by

$$\mu_N = \sigma\left[ln\left(\frac{1+2^{-1/\theta}}{1-2^{-1/\theta}}\right)\right](1+I_N);\, I_N\epsilon[I_L, I_U] \tag{3}$$

Scientific Method

The null and alternative hypotheses for the average traffic fatality are given below:

$H_0 : \mu_N = \mu_{0N}$ Vs. $H_1 : \mu_N \neq \mu_{0N}$

where μ_N is true average traffic fatality and μ_{0N} is the stipulated average traffic fatality. According to reports received, the developed sampling plan is declared as follows

Step-1: Choose a random sample of days n and document the average traffic fatality for these chosen locations. Stipulated the number of locations, say c, average traffic fatality μ_{0N} and indeterminacy constraint $I_N\epsilon[I_L, I_U]$.

Step-2: Accept $H_0 : \mu_N = \mu_{0N}$ if average traffic fatality in c locations is more than or equal to μ_{0N}, if not, reject $H_0 : \mu_N = \mu_{0N}$.

The projected sampling scheme is based on three parameters n, c and I_N, where $I_N\epsilon[I_L, I_U]$ is measured as the stipulated constraint and fix corresponding to the uncertainty intensity. Let $t_0 = d\mu_{0N}$ called as time in days, where d is denoted as termination ratio. The chance of accepting $H_0 : \mu_N = \mu_{0N}$ is given by

$$L(p) = \sum_{i=0}^{c}\binom{n}{i}p^i(1-p)^{n-i} \tag{4}$$

where p is the probability of rejecting $H_0 : \mu_N = \mu_{0N}$ and it is obtained from Eqs. (2) and (3) and it is defined by

$$p = \left\{\left(\frac{1-\exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)}{1+\exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)}\right)^{\theta}\right\} + \left\{\left(\frac{1-\exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)}{1+\exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)}\right)^{\theta}\right\}I_N. \tag{5}$$

Where $\vartheta = ln(\frac{1+2^{-1/\theta}}{1-2^{-1/\theta}})$, μ_N/μ_{0N} is the ratio of true average traffic fatality to stipulated average traffic fatality. Suppose that α and β be type-I and type-II errors. The highway authorities' are paying attention to concern the projected plan for examine $H_0 : \mu_N = \mu_{0N}$ such that the chance of accepting $H_0 : \mu_N = \mu_{0N}$ when it is true should be larger than $(1-\alpha)$ at μ/μ_0 and the chance of accepting $H_0 : \mu_N = \mu_{0N}$ when it is wrong should be smaller than $\tilde{\beta}$ at $\mu_N/\mu_{0N} = 1$. The plan constants for examine $H_0 : \mu_N = \mu_{0N}$ will be determined in such a way that the below two inequalities are fulfilled.

$$L(p_1|\mu_N/\mu_{0N} = 1) \leq \beta \tag{6}$$

$$L(p_2|\mu_N/\mu_{0N}) \geq 1-\alpha \tag{7}$$

Table 1
The plan parameter when $\alpha = 0.10; \theta = 1.5$ and $d = 0.50$.

β	$\frac{\mu_N}{\mu_{0N}}$	I_U=0.00			I_U=0.02			I_U=0.04			I_U=0.05		
		n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$
0.25	1.2	261	50	0.9002	256	50	0.9000	251	50	0.9009	248	50	0.9042
	1.3	137	25	0.9035	134	25	0.9059	131	25	0.9091	125	24	0.9027
	1.4	86	15	0.9049	90	16	0.9099	83	15	0.9031	82	15	0.9050
	1.5	66	11	0.9111	59	10	0.9028	58	10	0.9018	63	11	0.9106
	1.8	34	5	0.9144	34	5	0.9078	33	5	0.9117	33	5	0.9084
	2	29	4	0.9274	28	4	0.9314	28	4	0.9266	28	4	0.9242
0.10	1.2	453	84	0.9024	439	83	0.9010	435	84	0.9055	426	83	0.9035
	1.3	229	40	0.9023	225	40	0.9002	220	40	0.9041	218	40	0.9038
	1.4	151	25	0.9089	143	24	0.9004	140	24	0.9023	139	24	0.9003
	1.5	109	17	0.9048	107	17	0.9042	105	17	0.9041	104	17	0.9043
	1.8	59	8	0.9129	58	8	0.9119	57	8	0.9113	56	8	0.9149
	2	48	6	0.9207	47	6	0.9213	46	6	0.9222	46	6	0.9191
0.05	1.2	591	108	0.9012	574	107	0.9009	563	107	0.9012	557	107	0.9036
	1.3	298	51	0.9004	292	51	0.9015	292	52	0.9037	284	51	0.9005
	1.4	193	31	0.9003	189	31	0.9018	185	31	0.9040	183	31	0.9055
	1.5	144	22	0.9113	136	21	0.9004	133	21	0.9031	132	21	0.9016
	1.8	77	10	0.9085	76	10	0.9053	74	10	0.9092	73	10	0.9113
	2	60	7	0.9041	58	7	0.9102	57	7	0.9095	57	7	0.9056

Table 2
The plan parameter when $\alpha = 0.10; \theta = 1.5$ and $d = 1.00$.

β	$\frac{\mu_N}{\mu_{0N}}$	I_U=0.00			I_U=0.02			I_U=0.04			I_U=0.05		
		n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$
0.25	1.2	117	54	0.9001	108	51	0.9013	106	51	0.9018	105	51	0.9024
	1.3	61	27	0.9029	55	25	0.9049	54	25	0.9051	56	26	0.9019
	1.4	35	15	0.9038	37	16	0.9012	36	16	0.9090	36	16	0.9017
	1.5	27	11	0.9023	26	11	0.9149	26	11	0.9034	28	12	0.9126
	1.8	16	6	0.9295	16	6	0.9227	13	5	0.9152	13	5	0.9118
	2	12	4	0.9117	12	4	0.9053	11	4	0.9282	11	4	0.9257
0.10	1.2	193	87	0.9025	185	85	0.9003	182	83	0.9016	182	86	0.9019
	1.3	98	42	0.9026	96	42	0.9051	92	41	0.9029	91	41	0.9055
	1.4	64	26	0.9001	60	25	0.9037	59	25	0.9022	56	24	0.9012
	1.5	46	18	0.9108	45	18	0.9136	42	17	0.9038	44	18	0.9098
	1.8	26	9	0.9215	23	8	0.9067	25	9	0.9229	22	8	0.9156
	2	19	6	0.9137	19	6	0.9058	18	6	0.9208	18	6	0.9173
0.05	1.2	249	111	0.9021	242	110	0.9020	233	108	0.9021	231	108	0.9006
	1.3	128	54	0.9029	123	53	0.9045	121	53	0.9011	115	51	0.9027
	1.4	80	32	0.9010	78	32	0.9086	77	32	0.9022	76	32	0.9069
	1.5	58	22	0.9001	54	21	0.9020	53	21	0.9024	55	22	0.9068
	1.8	30	10	0.9090	32	11	0.9227	29	10	0.9074	29	10	0.9021
	2	23	7	0.9070	25	8	0.9296	22	7	0.9106	22	7	0.9065

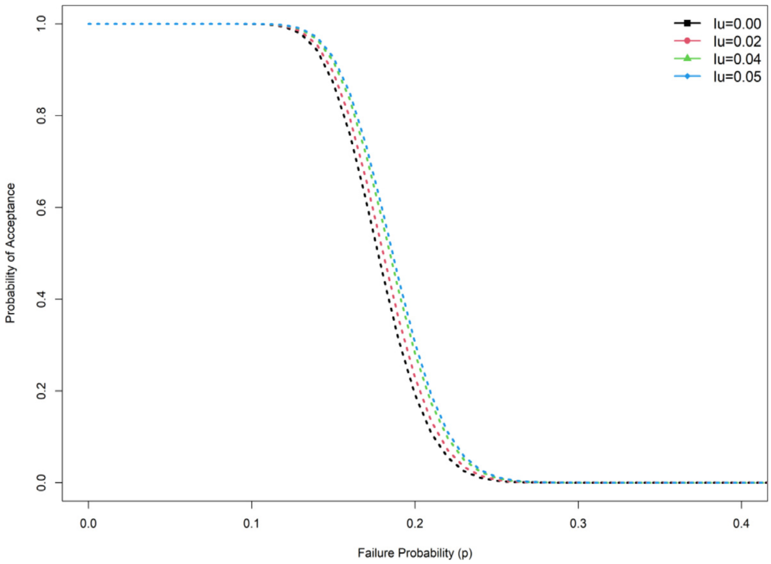

Fig. 1. OC curve plan at different indeterminacy values.

where p_1 and p_2 are defined by

$$p_1 = \left\{ \left(\frac{1 - \exp(-d\vartheta\,(1 + I_N))}{1 + \exp(-d\vartheta\,(1 + I_N))} \right)^{\theta} \right\} + \left\{ \left(\frac{1 - \exp(-d\vartheta\,(1 + I_N))}{1 + \exp(-d\vartheta\,(1 + I_N))} \right)^{\theta} \right\} I_N \tag{8}$$

and

$$p_2 = \left\{ \left(\frac{1 - \exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)}{1 + \exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)} \right)^{\theta} \right\} + \left\{ \left(\frac{1 - \exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)}{1 + \exp\left(-\frac{d\vartheta\,(1+I_N)}{\mu_N/\mu_{0N}}\right)} \right)^{\theta} \right\} I_N \tag{9}$$

The quantities of the plan constants n and c for several values of β, $\alpha = 0.10$, d and I_N are placed in Tables 1-4. Tables 1-2 are shown for the EHLD for $\theta = 1.5$ and Tables 2-4 for $\theta = 2$. From Tables, we conclude that the values of n decreases as the values of d increases from 0.5 to 1.0. Whereas, it is noticed that when the shape parameter increases from $\theta = 1.5$ *to* $\theta = 2$ the values of n decreases for other the same parameters are fixed. In addition, it is observed that the indeterminacy constant I_N also acting a considerable function to minimizing the sample size.

Table 3
The plan parameter when $\alpha = 0.10; \theta = 2$ and $d = 0.50$.

β	$\frac{\mu_N}{\mu_{0N}}$	I_U=0.00			I_U=0.02			I_U=0.04			I_U=0.05		
		n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$
0.25	1.2	212	32	0.9028	208	32	0.9024	204	32	0.9027	202	32	0.9031
	1.3	106	15	0.9026	104	15	0.9024	102	15	0.9026	101	15	0.9029
	1.4	68	9	0.9031	67	9	0.9008	72	10	0.9154	65	9	0.9018
	1.5	56	7	0.9166	54	7	0.9229	53	7	0.9228	53	7	0.9194
	1.8	29	3	0.9170	29	3	0.9121	28	3	0.9162	28	3	0.9139
	2	22	2	0.9178	22	2	0.9139	21	2	0.9194	21	2	0.9176
0.10	1.2	359	52	0.9016	352	52	0.9018	345	52	0.9030	342	52	0.9020
	1.3	187	25	0.9028	183	25	0.9046	180	25	0.9024	178	25	0.9039
	1.4	121	15	0.9047	119	15	0.9029	117	15	0.9015	115	15	0.9066
	1.5	87	10	0.9036	92	11	0.9204	84	10	0.9018	83	10	0.9032
	1.8	52	5	0.9225	51	5	0.9225	50	5	0.9227	50	5	0.9199
	2	45	4	0.9409	37	3	0.9002	36	3	0.9025	43	4	0.9404
0.05	1.2	471	67	0.9013	462	67	0.9008	453	67	0.9015	442	66	0.9002
	1.3	245	32	0.9035	240	32	0.9045	236	32	0.9023	233	32	0.9055
	1.4	158	19	0.9032	155	19	0.903	152	19	0.9033	151	19	0.9012
	1.5	117	13	0.9046	115	13	0.9033	112	13	0.9076	111	13	0.9073
	1.8	66	6	0.9150	65	6	0.9135	64	6	0.9122	63	6	0.9145
	2	51	4	0.9092	50	4	0.9093	49	4	0.9097	49	4	0.9068

Table 4
The plan parameter when $\alpha = 0.10; \theta = 2$ and $d = 1.00$.

β	$\frac{\mu_N}{\mu_{0N}}$	I_U=0.00			I_U=0.02			I_U=0.04			I_U=0.05		
		n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$
0.25	1.2	86	39	0.9000	82	38	0.9017	82	39	0.9012	82	39	0.9022
	1.3	44	19	0.9051	43	19	0.9092	42	19	0.9071	42	19	0.9062
	1.4	29	12	0.9158	28	11	0.9120	28	12	0.9190	28	12	0.9095
	1.5	18	7	0.9005	18	8	0.9145	17	7	0.9111	17	7	0.9071
	1.8	12	4	0.9191	9	3	0.9003	11	4	0.9221	11	4	0.9321
	2.0	10	3	0.9237	9	3	0.9438	9	3	0.9343	9	3	0.9383
0.10	1.2	145	64	0.9047	140	63	0.9039	113	50	0.9060	93	50	0.9070
	1.3	72	30	0.9086	71	30	0.9033	61	26	0.9204	51	26	0.9224
	1.4	46	18	0.9070	45	18	0.9098	39	16	0.9061	34	16	0.9067
	1.5	35	13	0.9174	32	12	0.9056	24	11	0.9290	24	11	0.9294
	1.8	19	6	0.9226	16	5	0.9004	13	5	0.9242	13	5	0.9247
	2.0	14	4	0.9234	14	4	0.9179	9	3	0.9083	9	3	0.9085
0.05	1.2	179	78	0.9003	178	79	0.9001	159	63	0.9012	119	63	0.9016
	1.3	93	38	0.9068	89	37	0.9024	75	32	0.9012	65	32	0.9010
	1.4	60	23	0.9094	59	23	0.9076	51	19	0.9065	41	19	0.9071
	1.5	42	15	0.9012	41	15	0.9053	30	13	0.9069	30	13	0.9061
	1.8	23	7	0.9173	23	7	0.9090	18	7	0.9272	18	7	0.9474
	2.0	18	5	0.9266	18	5	0.9205	15	5	0.9328	15	5	0.9330

Comparative studies

The aim of this section is that to study the effectiveness of the projected sampling plan with respect to sample size. The lesser the sample size is more economical for examine the hypothesis about the average traffic fatality. Make a note that the developed sampling plan is the oversimplification of the plan based on traditional statistics if no uncertainty or indeterminacy is establish while commemorating the average traffic fatality. When I_N=0, the developed sampling plan becomes the on hand sampling plan. In Tables 1–4 the first spell of column i.e. at I_N=0 are the plan parameter of the traditional or existing sampling plans.

The results from tables, we would conclude that the sample size is large in traditional sampling plan as compared with proposed sampling plan. The sample size comparison between the existing plan (I_N=0) and the proposed plan (I_N=0.05) are given in Table 5. For example, when $\alpha = 0.10, \beta = 0.25,\ \mu_N/\mu_{0N}$=1.2, θ=1.5 and d=0.5 from Table 5, it can be seen that n=261 from the plan under classical statistics and n=248 for the projected sampling plan. From this study, it is concluded that the projected plan under indeterminacy is efficient over the existing sampling plan under traditional statistics with respect to sample size. Operating characteristic (OC) curve of plan of the EHLD when $\alpha = 0.10; \theta = 1.5$ and $d = 0.50$ is depicted in Fig. 1. Therefore, the application of the proposed plan for testing the null hypothesis $H_0 : \mu_N = \mu_{0N}$ demands a lesser sample as compared to the on hand plan. The OC curve in Fig. 1 also shows the same performance. The highway authorities' can apply the proposed plan under uncertainty to save the time and money.

Table 5
Sample size comparison between existing and proposed plans.

β	$\frac{\mu_N}{\mu_{0N}}$	$\theta=2$, d=1.0		$\theta=2$, $d=0.50$		$\theta=1.5$, $d=1.0$		$\theta=1.5$, $d=0.5$	
		Existing	Proposed	Existing	Proposed	Existing	Proposed	Existing	Proposed
0.25	1.2	86	82	212	202	117	105	261	248
	1.3	44	42	106	101	61	56	137	125
	1.4	29	28	68	65	35	36	86	82
	1.5	18	17	56	53	27	28	66	63
	1.8	12	11	29	28	16	13	34	33
	2.0	10	9	22	21	12	11	29	28
0.10	1.2	145	93	359	342	193	182	453	426
	1.3	72	51	187	178	98	91	229	218
	1.4	46	34	121	115	64	56	151	139
	1.5	35	24	87	83	46	44	109	104
	1.8	19	13	52	50	26	22	59	56
	2.0	14	9	45	43	19	18	48	46
0.05	1.2	179	119	471	442	249	231	591	557
	1.3	93	65	245	233	128	115	298	284
	1.4	60	41	158	151	80	76	193	183
	1.5	42	30	117	111	58	55	144	132
	1.8	23	18	66	63	30	29	77	73
	2.0	18	15	51	49	23	22	60	57

Table 6
The plan parameter when $\alpha=0.10$; $\theta=0.9764$ and $d=0.50$.

β	$\frac{\mu_N}{\mu_{0N}}$	I_U=0.00			I_U=0.02			I_U=0.04			I_U=0.05		
		n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$
0.25	1.2	404	103	0.9054	385	100	0.9008	381	101	0.9043	374	100	0.9018
	1.3	206	51	0.9075	202	51	0.9079	191	49	0.9002	185	48	0.9009
	1.4	125	30	0.9019	127	31	0.9024	124	31	0.9075	119	30	0.9037
	1.5	90	21	0.9035	92	22	0.9118	87	21	0.9000	86	21	0.9020
	1.8	51	11	0.9122	50	11	0.9126	45	10	0.9008	48	11	0.9194
	2	39	8	0.9130	38	8	0.9161	33	7	0.9023	37	8	0.9156
0.10	1.2	-	-	-	-	-	-	-	-	-	-	-	-
	1.3	343	82	0.9012	336	82	0.9032	328	81	0.9000	327	82	0.9009
	1.4	217	50	0.9019	213	50	0.9009	209	50	0.9008	207	50	0.9011
	1.5	157	35	0.9058	150	34	0.9003	147	34	0.9016	150	35	0.9037
	1.8	84	17	0.9068	82	17	0.9102	81	17	0.9056	80	17	0.9078
	2	63	12	0.9039	62	12	0.9019	60	12	0.9102	60	12	0.9048
0.05	1.2	-	-	-	-	-	-	-	-	-	-	-	-
	1.3	454	107	0.9013	441	106	0.9007	428	105	0.9024	420	104	0.9012
	1.4	287	65	0.9028	277	64	0.9021	272	64	0.9008	265	63	0.9007
	1.5	202	44	0.9004	198	44	0.9012	194	44	0.9029	192	44	0.9041
	1.8	107	21	0.9010	105	21	0.9007	103	21	0.9009	102	21	0.9013
	2	81	15	0.9035	84	16	0.9145	78	15	0.9032	77	15	0.9056

(-) represents parameters do not exist

Applications for traffic fatality data

Present section deals with the application of the proposed sampling plan for the exponentiated half logistic distribution under the indeterminacy is obtained using a real example. A real data of traffic fatalities happened in 2018 at South Carolina, USA were collected from https://www-fars.nhtsa.dot.gov/States/StatesCrashesAndAllVictims.aspx. These data set were reported by National Highway Traffic Safety Administration (NHTSA), USA. The traffic fatalities are immense and play a vital role on national highways in different countries. Owing the unpredictability and uncertainty, the traffic fatality data comes from the statistical distribution under neutrosophic statistics. The highway authorities' are concerned to observe the daily or location wise average traffic fatality under indeterminacy. The traffic fatality data of South Carolina for 2018 is taken from NHTSA reports and for ready reference given below.

Traffic fatality in different locations: 1, 1, 2, 3, 3, 3, 4, 5, 8, 8, 8, 9, 9, 9, 10, 11, 11, 12, 12, 12, 13, 15, 15, 16, 16, 17, 18, 20, 20, 22, 22, 23, 23, 25, 32, 34, 35, 39, 43, 44, 50, 66, 68, 71, 72 and 77.

It is establish that the traffic fatality data comes from the EHLD with shape parameter $\hat{\theta}=0.9764$ and scale parameter $\sigma=16.6092$ and the maximum distance between the real time data and the fitted of EHLD is found from the Kolmogorov-Smirnov test as 0.1106 and also the p-value is 0.6271. The demonstration of the goodness of fit for the given model is shown in Fig. 2, the empirical and theoretical cdfs and Q-Q plots for the EHLD for the traffic fatality data.

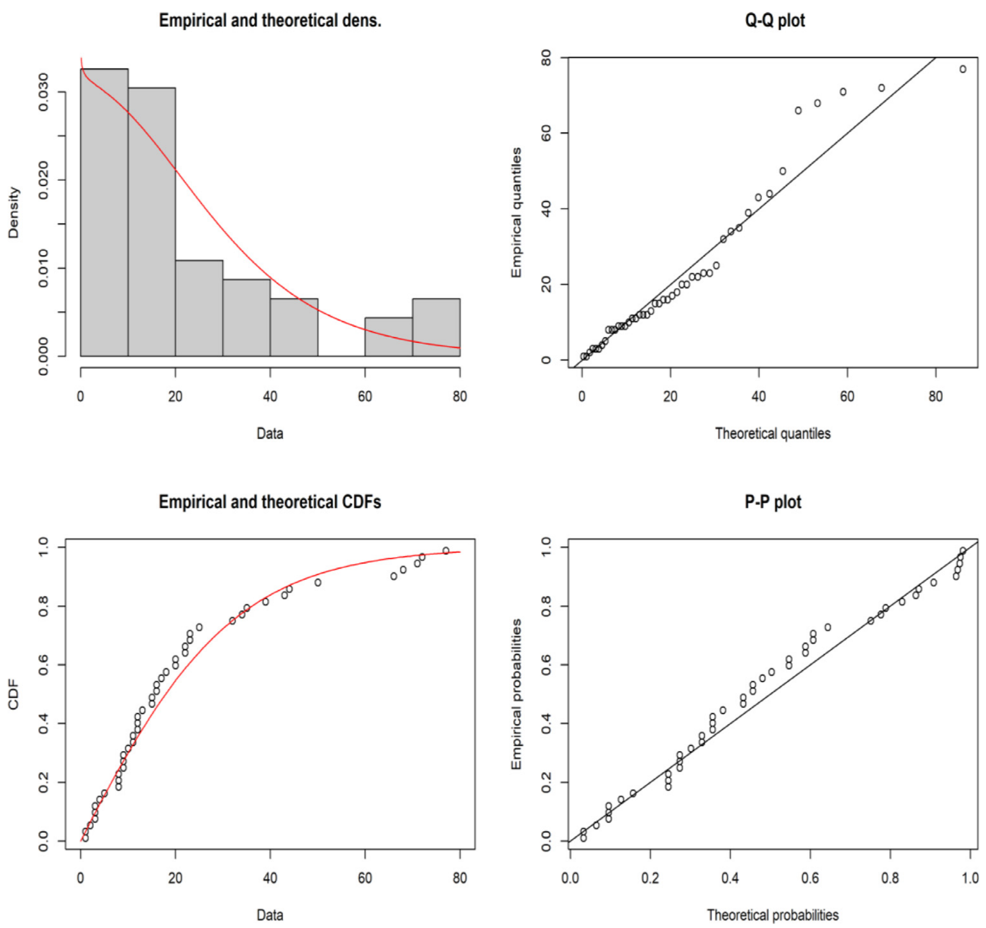

Fig. 2. The empirical and theoretical pdf, cdfs, Q-Q and P-P plots for the EHLD for the traffic fatality data.

Table 7
The plan parameter when $\alpha = 0.10$; $\theta = 0.9764$ and $d = 1.00$.

β	$\frac{\mu_N}{\mu_{0N}}$	I_U=0.00			I_U=0.02			I_U=0.04			I_U=0.05		
		n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$	n	c	$L(p_1)$
0.25	1.2	199	94	0.9021	191	92	0.9011	189	88	0.9007	183	91	0.9089
	1.3	100	46	0.9047	96	45	0.9027	92	44	0.9032	89	43	0.9028
	1.4	65	29	0.9033	66	30	0.9063	58	27	0.9035	62	29	0.9050
	1.5	46	20	0.9043	45	20	0.9076	42	19	0.9030	44	20	0.9034
	1.8	25	10	0.9041	24	10	0.9176	24	10	0.9071	24	10	0.9015
	2	18	7	0.9134	18	7	0.9044	20	8	0.9184	17	7	0.9194
0.10	1.2	-	-	-	-	-	-	-	-	-	-	-	-
	1.3	168	75	0.9007	167	76	0.9024	159	72	0.9008	158	74	0.9017
	1.4	109	47	0.9027	102	45	0.9046	98	44	0.9011	97	44	0.9028
	1.5	79	33	0.9057	75	32	0.9058	69	30	0.9006	73	32	0.9054
	1.8	39	15	0.9078	41	16	0.9099	40	16	0.9149	37	15	0.9131
	2	33	12	0.9144	30	11	0.9015	29	11	0.9115	29	11	0.9059
0.05	1.2	-	-	-	-	-	-	-	-	-	-	-	-
	1.3	220	97	0.9004	211	95	0.9023	205	94	0.9003	203	94	0.9016
	1.4	141	60	0.9052	136	59	0.9042	129	57	0.9005	130	58	0.9031
	1.5	100	41	0.9018	93	39	0.9021	96	41	0.9064	93	40	0.9014
	1.8	51	19	0.9012	50	19	0.9021	49	19	0.9038	48	19	0.9136
	2	40	14	0.9004	39	14	0.9053	38	14	0.9107	35	13	0.9044

(-) represents parameters do not exist

The plan parameters for this shape parameter are shown in Tables 6-7. For the proposed plan, the shape parameter is $\hat{\theta}_N = (1 + 0.04) \times 0.9764 \approx 1.0155$ when I_U=0.04. Suppose that highway authorities' are concerned to test $H_0 : \mu_N = 17.8812$ with the aid of the proposed sampling plan when I_U=0.04, $\alpha = 0.10$, $\mu_{\mathrm{N}}/\mu_{0\mathrm{N}}$=1.8,$d$=0.5 and β=0.25. From Table 6, it can be noted that n=45 and c=10. The projected sampling plan will be employed as: accept the null hypothesis $H_0 : \mu_N = 17.8812$ if average traffic fatality in 10 locations is more than equal to 17.8812 cases. From the data, it can be noted average traffic fatality is greater than equal to 17.8812 cases in more than 10 localities, therefore, the claim about the average traffic fatality $H_0 : \mu_N = 17.8812$ will be accepted. Using the real world illustration, it is accomplished that the projected sampling will be obliging to check the average traffic fatality. Moreover, from real example it is noticed that from Table 6, the sample size for the proposed plan has 374 whereas existing plan sample size at I_U=0.0 is 404. It shows that based on real data the proposed sampling plan is more efficient than the existing sampling plans.

Concluding remarks

Under the indeterminacy, exponentiated half logistic distribution was taken into consideration to build a time-truncated sampling plan. The suggested design parameters were created by adjusting the indeterminacy parameter and form values. Different amounts of form value and indeterminacy quantities were accommodated by the quantities of the produced design. Several tables were offered to help implement the suggested approach. The output of the results shows that sample size amounts decrease as indeterminacy amounts increase. As a result, the indeterminacy parameter is crucial for fixing the design numbers. Based on statistics on road fatalities, the devised sampling plan's application in the real world was depicted. As compared to the available classical sampling plan, it is also concluded that the recommended design is advantageous for examining the average fatal accidents at a smaller sample size. It has been advised to use the proposed sampling plan under indeterminacy to evaluate the average number of road fatalities because it is more cost-effective. The created plan might be used to evaluate big data analytics starting with health research, traffic accidents, ecology, and other areas that could be expanded. The thought-out strategy would be lengthened to account for different lifetime distributions and additional sample plans as future investigation.(Table 3)

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