https://africanjournalofbiomedicalresearch.com/index.php/AJBR
Afr. J. Biomed. Res. Vol. 28(2s) (February 2025); 425-444
Research Article

Evaluating Distribution Fitting Methods for Predicting Child Growth Parameters: A Comparative Analysis across Various Distributions

T. Manjusha[1, 2], P. Pranay[3*], B. Navatha[4], V.V. Haragopal[5]

[1]Research Scholar, Department of Mathematics and Statistics, Chaitanya (Deemed to be) University Kishanpura, Hanamkonda Telangana, India
[2]Assistant Professor, Department of Statistics, Little Flower Degree College, Uppal, Hyderabad Telangana, India, tmanjusha99@gmail.com
[3*]Associate Professor, Department of Mathematics and Statistics, Chaitanya (Deemed to be) University Kishanpura, Hanamkonda Telangana, India, pettempranay@gmail.com
[4]Assistant Professor, Department of Mathematics, Presidency University, Bengaluru, navatha.b@presidencyuniversity.in
[5]Professor, Department of Statistics, BITS Pilani, Hyderabad, haragopal_vajjha@yahoo.com.

***Corresponding Author:** P.Pranay
*Associate Professor Department of Mathematics and Statistics Chaitanya (Deemed to be) University Kishanpura, Hanamkonda, Telangana, India

Abstract: This paper attempts to fit statistical distributions to the data obtained from the NFHS-5 dataset to understand the relationship between child height, weight, and age. The objective is to identify the best-fit distributions to represent these growth characteristics to have a deeper comprehension of the development trajectory of children. 18 different statistical distributions had to be fitted, and the Anderson-Darling, Chi-Square, and Kolmogorov-Smirnov one-sample tests were applied to check the goodness of fit. The findings indicate that the overall Pareto distribution best matches age, the general extreme value (GEV) fits weight, and the general gamma (4P) distribution best fits height. The findings were further supported by descriptive statistics, which illustrated the data's skewness, variability, and kurtosis. This type of comprehensive distributional modeling has clearly illustrated the intricate interrelations between biological, dietary, and socioeconomic variables affecting growth, so even small deviations from expected trajectories indicate substantial risks of stunting, undernutrition, or obesity. Such findings would have immense potential to help improve health outcomes in children through enhanced pediatric health research by creating better predictions and more concentrated interventions. By using advanced statistical distribution fitting to NFHS-5 data, this work is unique in that it finds particular best-fit models for height, weight, and age. These disclosures advance knowledge of child development trends and aid in the early identification of concerns such as stunting or undernutrition.

Key Words: Child weight, Kolmogorov-Smirnov test, Anderson-Darling test, Chi-Square test, Probability Distribution.

Received: 22/01/2025 Accepted: 01/02/2025

DOI: https://doi.org/10.53555/AJBR.v28i2S.6590

© 2025 The Author(s).
This article has been published under the terms of Creative Commons Attribution-Noncommercial 4.0 International License (CC BY-NC 4.0), which permits noncommercial unrestricted use, distribution, and reproduction in any medium, provided that the following statement is provided. "This article has been published in the African Journal of Biomedical Research"

1. Introduction

In India, child development is the biological, psychological, and emotional changes that children undergo in becoming adults. Child developments greatly affect overall health in India's population. There is a very important role for healthy growth and development of health in babies and young children to obtain general well-being along with future success [Yuniarti S 2021]. A child's development capacity is the yardstick by which the physical and nutritional health of a child can be assessed, for it reflects access to a healthy diet, medical treatment, and surroundings.

Indicators of growth and development of a child are often reflective of overall health and well-being [Putri S A et al. 2022]. Correct assessment of a child's weight, height, and age is important in determining whether or not a child is suffering from health issues or growing on the right trajectories [Fitria TN et al. 2023]. Childhood growth indicators, weight, height, and age have been an issue of much discussion in the literature. For instance, Maharlouei et al. state that birth weight correlates significantly with early childhood stunting and underweight growth outcomes; hence early nutritional status is considered quite important [Maharlouei et al. 2020]. Similarly, Fitria's study emphasizes a direct relationship between birth weights with later growth patterns, thus confirming that early measures of growth predict later health conditions [Fitriani N 2018]. Results of this study point out the consideration of weight along with height in the assessment of child growth.

The statistical methods applied in the study find their basis in well-established practice within the discipline. For example, the Kolmogorov-Smirnov test is known to be useful for comparing empirical distributions and goodness-of-fit tests [Xie et al. 2023]. Combination with Anderson-Darling and Chi-Square tests gives a holistic perspective in determining how appropriately these models may describe the child growth data dynamics. For example, the Chi-Square test has been extremely popularly applied in health-related studies to determine the interactions of categorical variables [Rahman et al. 2023], [Atif et al. 2023].

Fitting several statistical distributions is the primary goal of the study to identify the best models for forecasting a child's age, weight, and height. The best models for each parameter are identified using goodness of fit tests.

2. Resources and Techniques

2.1 Data and Research field

The present study has based itself on the results of the National Family Health Survey (NFHS-5), which took place between 2019 and 2021. This is considered the most superior source of the survey since it offers a detailed dataset for the exploration of inferences about factors with health-related issues. While analyzing the data on production, users may seek to characterize its behavior by fitting it to a certain probability distribution. Such a process generally comprises analyzing distributions that fall into one of three categories. These include semi-parametric, non-parametric, or parametric primary types. For this research, however, we will only review the focus on parametric and non-parametric distributions. Once there is identification of potential distributions, the best fit for the dataset should be derived. This is done by fitting each distribution's probability density function to the information and then applying goodness-of-fit tests to estimate their performance. These tests give the necessary details about the data's best match through the determination of the distribution that best explains the observed data, indicating the underlying production process.

2.2 Methods

The fitting of the distributions involved assessing 18 distributions: Beta, Gamma distribution, Gamma 3-parameter, General Extreme Value, General Gamma, General Gamma 4-parameter, Gumbel Max, Gumbel Min, log-Gamma, Log-Logistic, Log-Logistic 3-parameter, Logistic, Lognormal, Lognormal 3-parameter, Normal, Pareto 2, Weibull, and Weibull 3-parameter. A few of the distributions are given below.

2.2.1 Log-Logistic Distribution

α- shows shape (α>0)

β- Shows scale (β>0)

ϒ- Shows location

3-parameter Log-Logistic Distribution

p.d.f. is given as,

f (x)= $\frac{\alpha}{\beta}\left(\frac{x-y}{\beta}\right)^{\alpha-1}\left(1+\left(\frac{x-y}{\beta}\right)^{\alpha-2}\right)$; ϒ≤x<+∞

2.2.2 Beta Distribution

The p.d.f. of the Beta distribution is given by

f (x; α,β) = $\frac{x^{\alpha-1}\,(1-x)^{\beta-1}}{B(\alpha,\beta)}$

Where

x is the variable

α and β show shape parameters, and B(α,β) is the beta function given as B(α,β)= $\int_0^1 t^{\alpha-1}(1-t)^{\beta-1}$ dt

2.2.3 Generalized Gamma distribution

k- shows shape (k>0)

α- shows shape (α>0)

β-shows scale (β>0)

ϒ-shows location

4-Parameter Generalized gamma distribution p.d.f. is given by

f(x)= $\frac{k(x-\Upsilon)^{k\alpha-1}}{\beta^{k\alpha}\Gamma(\alpha)}$exp(-((x- ϒ)/β)^k); ϒ≤x≤+∞

2.2.4 Kolmogorov-Smirnov test

This test determines if the sample is drawn from a continuous distribution that is assumed. The idea of the statistical average distribution function serves as its main foundation. Let us suppose a distribution for CDF is denoted by F, and let a random sample be considered with a sample size n; as shown by the actual CDF, it is

$F_n(x)=\frac{1}{n}$(number of values ≤ x]

Definition:

The greatest vertical discrepancy between the theoretical and statistical cumulative distribution function is the foundation for the Kolmogorov-Smirnov statistics (D).

$D=\text{Max.}_{1\leq i\leq n}\left[F(X_i)-\frac{i-1}{n},\frac{i}{n}-F(x_i)\right]$

2.2.5 Anderson Darling test

A General test to see if some obtained average distribution function matches the projected cumulative distribution function is the Anderson-Darling technique. Compared to the Kolmogorov-Smirnov test, it gives the tales greater weight. A^2 is used to indicate it, and it is provided as

$A^2 = -n\,\frac{1}{n}\sum_{i=1}^{n}\;(2i-1)[\ln F(x_i)+\ln(1-F(x_{n-i+1}))]$

2.2.6 Chi-square tests

[Ermakov et al. 2021]. The definition of the chi-square is provided as

$\chi^2 =\sum_{i=1}^{k}\;\frac{(O_i-E_i)^2}{E_i}$ Where O_i is the real frequency and E_i is the predicted frequency.

3. Results

3.1 Descriptive Statistics

From Table 1, we can observe that the statistical summaries indicate huge differences in kid demographics between the datasets, comparing age, weight, and height. Child weight has a right-skewed distribution with large tails, and that of child height has a severely skewed distribution with heavy tails. In contrast to this, childhood portrays a more or less symmetrical distribution with light tails. They emphasize the importance of understanding multiple features of a child's growth parameter in finding patterns and possible influences that may affect their development [Yoon and Kim 2018].

3.2 Probability Density Function plots for child height, weight, and age

Results for the most optimal fit distribution of probabilities for child weight, height, and age are recorded in this section. Probability density function graphs, some of which are shown in pictures, are used to depict the eighteen distinct probability distributions that were used to predict the child data. The PP and QQ plots show a relatively straight line with points closely following the diagonal, indicating that the data likely follows the assumed distributions. The following are the best-fit distributions: General Gamma 4-parameter, Gen. Pareto, Log-Logistic 3-parameter, General Extreme Value, and Log-Normal 3-parameter.

Table 1: Descriptive Statistics of child Height, weight and age

	Height			Weight			Age		
Statistic	Value	Percentile	Value	Value	Percentile	Value	Value	Percentile	Value
Sample Size	1023	Min	200	327	Min	5	60	Min	0
Range	1200	5%	326.4	773	5%	23.4	59	5%	2.1
Mean	801.51	10%	392.7	189.31	10%	39.8	30	10%	5.1
Variance	91670.0	25% (Q1)	547	20094	25% (Q1)	89	305	25% (Q1)	14
Std. Deviation	302.77	50% (Q2)	803	141.75	50% (Q2)	171	17	50% (Q2)	30
Coeff. of Variation	0.37775	75% (Q3)	1059	0.74877	75% (Q3)	254	1	75% (Q3)	45
Std. Error	9.4662	90%	1212.6	7.839	90%	310.2	2	90%	54
Skewness	-0.02885	95%	1266.8	1.7946	95%	423.4	0	95%	57
Excess Kurtosis	-1.0856	Max	1400	4.6553	Max	778	-1	Max	59

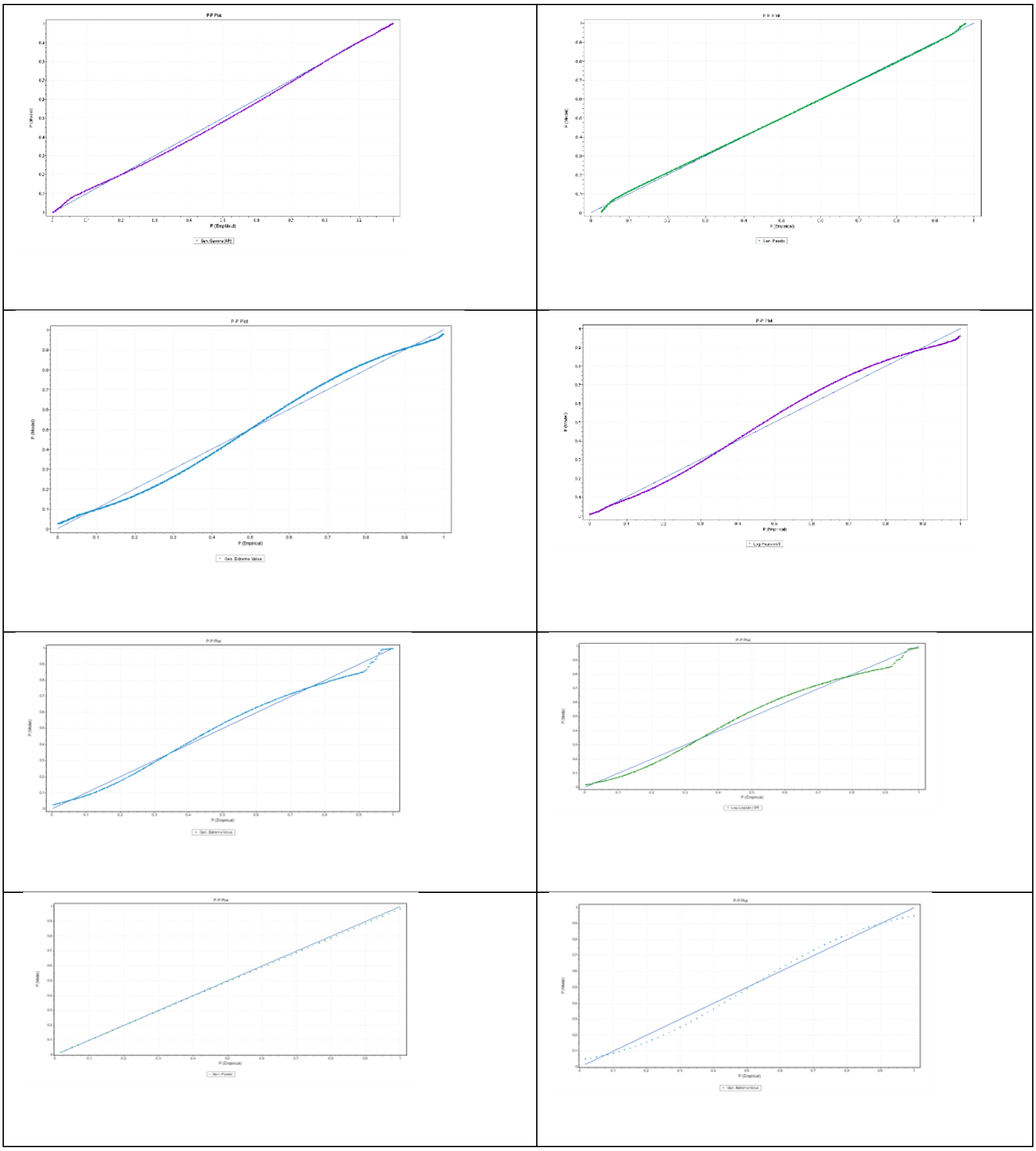
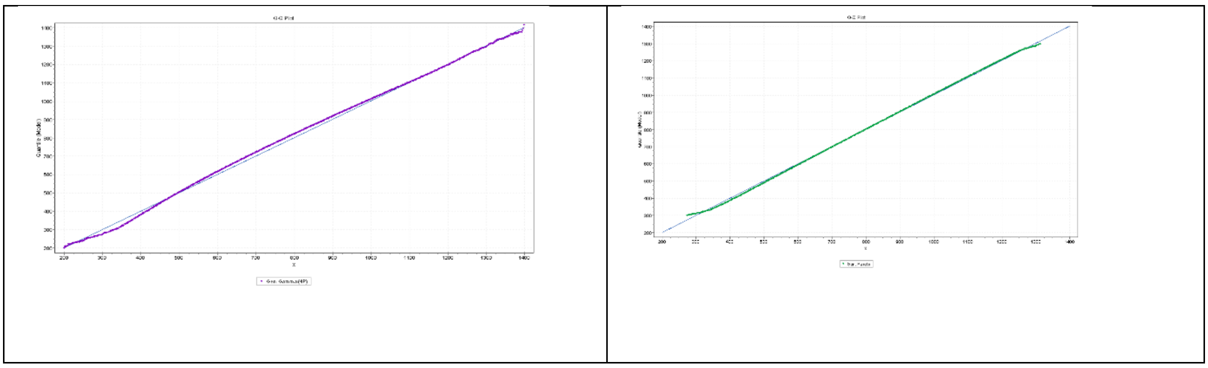


Figure 1: PP plots of General Gamma (4P), General Pareto, Log-Logistic (3P), Gen Extreme value, Log normal (3P) to the parameter Child height, weight, and age



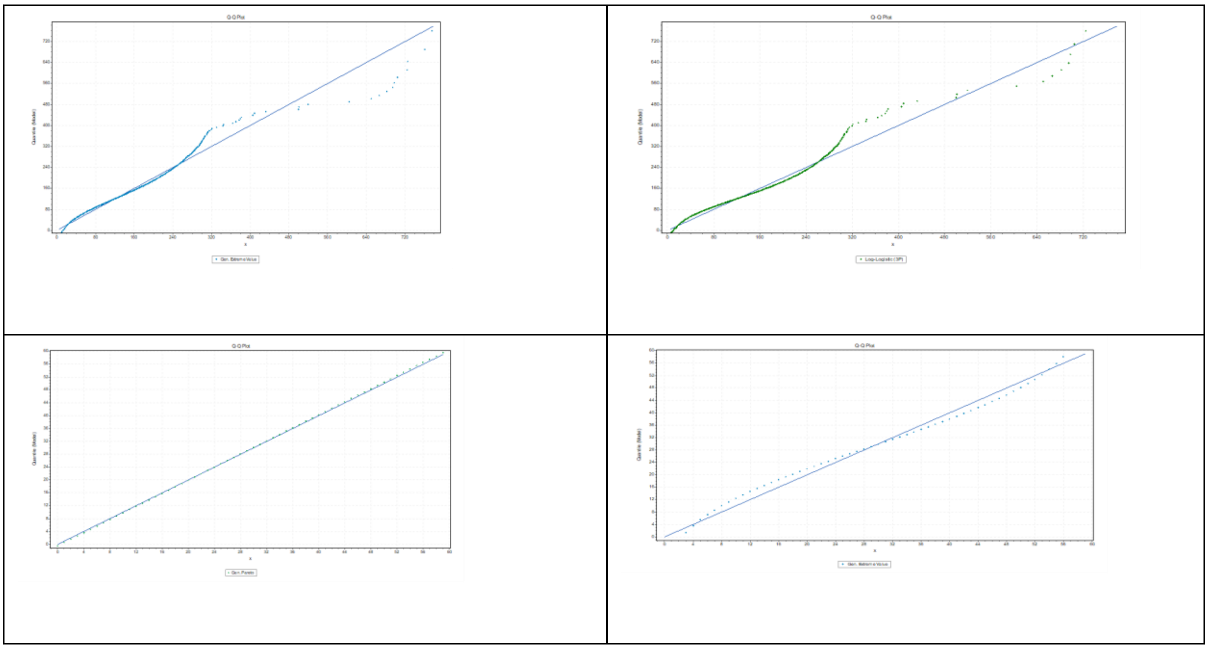


Figure 2: QQ plots of General Gamma 4-parameter, General Pareto, Log-Logistic 3-parameter, General Extreme value, Log normal 3-parameter to the parameter Child height, weight, and age

3.3 Goodness–of–Fit for various distributions

This section uses goodness-of-fit tests including A-D, K-S, and Chi-square to assess the adequacy of 18 statistical distributions to describe child development data.

Table 2: Summary Goodness –of- Fit for various distributions: Child height

S.No.	Distribution	K-S test		A-D test		χ^2 -test	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Chi-Squared	0.40107	25	6388.9	26	3136.3	25
2	Chi-Squared (2P)	0.05382	7	8.3089	7	47.297	6
3	Exponential	0.29126	22	171.28	22	779.34	22
4	Exponential (2P)	0.1897	21	97.085	20	311.88	20
5	Gamma	0.0784	15	15.99	13	84.478	17
6	Gamma (3P)	0.05999	12	8.8184	10	48.95	9
7	Gen. Extreme Value	0.04081	3	5.5434	2	29.522	2
8	Gen. Gamma	0.07316	13	11.9	12	55.082	12
9	Gen. Gamma (4P)	0.02259	**1**	1.1477	**1**	12.389	**1**
10	Gen. Pareto	0.02673	2	104.15	21	N/A	
11	Log-Gamma	0.09124	18	19.493	18	79.326	16
12	Log-Logistic	0.09521	19	18.625	17	76.928	15
13	Log-Logistic (3P)	0.05514	9	9.8907	11	52.19	11
14	Log-Pearson 3	0.0514	4	6.658	4	30.946	3
15	Logistic	0.0758	14	16.594	14	102.03	18
16	Lognormal	0.08422	16	16.655	15	69.104	14
17	Lognormal (3P)	0.05798	11	8.8022	9	49.921	10
18	Normal	0.05341	6	8.2789	6	47.701	7
19	Pareto	0.30941	24	203.86	24	675.72	21
20	Pareto 2	0.29133	23	171.4	23	788.71	23

21	Weibull	0.05164	5	6.4021	3	34.375	4
22	Weibull (3P)	0.05437	8	7.6801	5	43.558	5

Table 3: Summary Goodness –of- Fit for various distributions: Child weight

S.NO.	Distribution	K-S test		A-D test		χ^2 -test	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Beta	0.077	7	2.318	9	21.44	10
2	Gamma	0.076	5	2.307	7	20.64	8
3	Gamma (3P)	0.077	6	2.313	8	20.64	7
4	General Extreme Value	0.063	**1**	1.605	**1**	17.18	4
5	General Gamma	0.075	4	2.326	10	21.23	9
6	General Gamma (4P)	0.08	10	2.257	5	17.86	5
7	Gumbel Max	0.079	8	2.393	11	11.62	**1**
8	Gumbel Min	0.129	17	38.21	18	33.26	14
9	Log-Gamma	0.124	16	10.56	16	78.03	18
10	Log-Logistic	0.105	15	6.617	13	64.17	16
11	Log-Logistic (3P)	0.063	2	2.165	4	28.34	13
12	Logistic	0.086	12	6.491	12	12.34	2
13	Lognormal	0.1	13	6.853	14	56.84	15
14	Lognormal (3P)	0.066	3	2.062	3	23.1	11
15	Normal	0.103	14	8.96	15	26.55	12
16	Pareto 2	0.133	18	13.94	17	75.26	17
17	Weibull	0.079	9	2.04	2	14.88	3
18	Weibull (3P)	0.081	11	2.281	6	18.46	6

Table 4: Summary Goodness –of- Fit for various distributions: Child age

S. No.	Distribution	K-S test		A-D test		χ^2 -test	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Chi-Squared	0.26218	16	45.468	16	46.778	16
2	Chi-Squared	0.36893	17	51.901	17	63.128	17
3	Exponential	0.15927	11	5.2695	13	6.1065	11
4	Exponential (2P)	0.15927	12	3.8256	7	6.1065	12
5	Gamma	0.10662	7	4.5467	11	6.8896	14
6	General Gamma	0.09737	6	3.3047	6	3.8307	5
7	General Extreme Value	0.05131	2	0.46111	2	1.5369	2
8	General Pareto	0.01639	**1**	0.0431	**1**	0.12516	**1**
9	Log-Logistic	0.15005	10	3.9771	8	4.5034	6
10	Log-Logistic	0.1919	13	5.7082	14	6.4212	13
11	Logistic	0.08585	5	1.154	4	5.405	10

12	Lognormal	0.1435	8	4.4562	10	4.6077	8
13	Lognormal (4P)	0.14351	9	4.4561	9	4.6075	7
14	Normal	0.06357	3	0.64345	3	2.9266	3
15	Pareto 2	0.19547	15	6.6534	15	9.9678	15
16	Weibull	0.19471	14	4.6947	12	4.9724	9
17	Weibull(3P)	0.08028	4	3.0918	5	3.4048	4

4. Discussion

The best-fitting distributions for the NFHS-5 child data are selected based on the unique characteristics of each growth parameter, such as age, weight, and height, and also with the help of descriptive data, which gives a deeper understanding of these parameters.

Height Distribution: (From Table 2) The General Gamma (4P) distribution that best matched height was discovered, which reflects the effect of hereditary and environmental factors on growth [Bourguignon M et al. 2013]. Variations in growth paths are well captured by this distribution in modeling positively skewed biological data, such as height. These trends reflect how vital health and nutrition are at crucial stages of growth. Descriptive statistics group most children around median height, though variability manifests the effects of outside factors, such as parental health and socioeconomic status.

Weight Distribution: As mentioned earlier (From Table 3) the General Extreme Value distribution was the best for weight. The weight distribution tail describes the children vulnerable to malnutrition (the lower tail) or obesity (the higher tail). Such extremes may be associated with dietary habits, level of physical activity, genetic predispositions, and socio-economic conditions [Abdelall Y 2023], [Hassan AS 2019]. These extremes can provide useful information for focused treatments to address childhood hunger and obesity. It is observed that a greater percentage of youngsters are at the extremes, as indicated by the descriptive statistics, as there is more skewness for weight than height.

Age Distribution: The General Pareto distribution represents age because some age ranges have an abnormally high influence on growth outcomes (Table 4). The long tail in the age distribution in this dataset represents the older children, which emphasizes a need to concentrate on key age ranges where interventions maximize impacts on development and growth [Jocković J 2011]. This is consistent with the fact that biological, dietary, and environmental factors often covary with age-specific growth spurts or plateaus [Gau CC 2021].

Besides the fitted distributions, the descriptive analysis provides an in-depth understanding of the outlying observations and heterogeneity in child growth measurements [Huang N et al. 2023]. The complexity of growth trends and the need for effective monitoring and intervention approaches is underscored by this combination of descriptive and distributional analysis [Hiremath M et al. 2023].

5. Conclusion

Overall, these results reveal the complexity of growth and development in the child, with implications that suggest the patterns observed here for height, weight, and age distributions may be the result of multiple mechanisms, such as, but not limited to, genetic, environmental, nutritional, and lifestyle influences; more investigation and analysis are needed to understand the natures of key elements and their effects on the health and welfare of children.

The fitted distributions serve as powerful tools to describe, follow, and predict child growth trends. They empower data-driven choices in public health by providing an effective mathematical tool to represent variability and hazard estimation. A detailed description of growth curves is feasible by applying the General Gamma (4P) in the description of height curves, the General Extreme Value for the description of the weight curve, and, lastly, the General Pareto in describing age trends. These metrics depict the effects of biological, environmental, and socioeconomic variables.

This can be used efficiently in monitoring children at the tails of the weight distribution for risks of obesity or malnutrition by identifying those using thresholds from the GEV model and validating them against health benchmarks such as WHO guidelines. These results indicate the overall child health as they highlight the importance of connecting observed development patterns to important variables. Researchers and politicians would be able to create specific plans to encourage healthy growth, as well as deal with possible problems early, by making use of these statistical models that will eventually help children develop and flourish.

Conflict of Interest

As the study's authors, we thus declare that there are no conflicts of interest in its findings or the preparation of this manuscript. All authors have contributed to this work without any external influences that could compromise the integrity of the study or its outcomes.

Acknowledgments

The author would like to thank the Demographic Health Survey.

References

1. Abdelall Y (2023). A New Inverse Pareto Distribution. Asian Journal of Probability and Statistics, **21(2)**:22-34.

2. Atif, M., Farooq, M., Shafiq, M., Ayub, G. and Ilyas, M., (2023). The impact of partner's behavior on pregnancy-related outcomes and safe childbirth in Pakistan. BMC Pregnancy and Childbirth, **23(1)**, p.516.
3. Bourguignon M, Silva RB, Zea LM, Cordeiro GM (2013). The Kumaraswamy Pareto distribution. Journal of statistical theory and applications, **12(2)**:129-44.
4. Ermakov, Mikhail (2021). Chi-squared test for hypothesis testing of homogeneity. arXiv preprint arXiv, 2180.11980
5. Fitria TN, Umijati S, Irmawati M (2023).The Correlation between Birth Weight and Child Growth Aged 3-12 Months at Lekok Health Centers in Pasuruan Regency. IJRP.ORG, **138(1)**,112-118.
6. Fitriani N (2018).Hubungan Kunjungan Ibu ke Posyandu dengan Jumlah Balita Bawah Garis Merah (BGM) di Desa Tente Kecamatan Woha Kabupaten Bima. Palapa
7. **6.1**:69-80.
8. Gau CC, Yao TC, Gan ST, Lin SJ, Yeh KW, Chen LC, Ou LS, Lee WI, Wu CY, Huang JL (2021).Age, gender, height, and weight about joint cartilage thickness among school-aged children from ultrasonographic measurement. Pediatric Rheumatology, **19(1)**:71.
9. Hassan AS, Elgarhy M, Mohamd RE, Alrajhi S (2019). On the alpha power transformed power Lindley distribution. Journal of Probability and Statistics. **2019(1)**:8024769.
10. Hiremath M, Walvekar P, Baliga S (2023). Prevalence of undernutrition among under-five children and correlation between anthropometry of parents and anthropometry of children. Journal of Krishna Institute of Medical Sciences (JKIMSU), **12(3)**.
11. Huang N, Yang F, Liu X, Bai Y, Guo J, Riem MM (2023).The prevalences, changes, and related factors of child maltreatment during the COVID-19 pandemic: A systematic review. Child Abuse & Neglect, **135**:105992.
12. Jocković J, Mladenović P (2011). Coupon collector's problem and generalized Pareto distributions. Journal of Statistical Planning and Inference**,** **141(7)**:2348-52.
13. Maharlouei, Najmeh, Sogand Farhangian, Hadi Raeisi Shahraki, Abbas Rezaianzadeh, and Kamran Bagheri (2021) Comparing Growth and Development of Low and Normal Birth Weight Children at Age of 60 Months. Shiraz e-medical journal, Vol **22**, issue 8; e107126.
14. Majid R, Kalza LA, Erawan PE, Saktiansyah LA, Rezal F, Al Rajab M (2023). Factors associated with compliance payments patient social assurance administrative agency of health independent participants in the hospital Kendari city southeast Sulawesi province Indonesia.World journal of advanced research and reviews, **20(1)**, 072-078.
15. Putri SA, Sebba AK, Asmuni A (2022).The Determinants of Stunting Incidence in Children Aged 24-59 Months. Jurnal Ilmu Kesehatan Masyarakat, **13(3)**:306-20.
16. Xie, Linchen, Ran Guo, Limin Yang, Yukihiro Ozaki, Isao Noda, Yizhuang Xu, and Kun Huang (2023). A new approach to recognizing the correct pattern of cross-peaks from a noisy 2D asynchronous spectrum by detecting intrinsic symmetry via the Kolmogorov–Smirnov test. Physical chemistry chemical physics, **25.18**: 12863-12871.
17. Yoon, Heun-Keung, and Kim (2018). The Impact of Atopic Dermatitis on Children's Sleep Duration and Their Mother's Suicidal Ideation. Global Journal of Health Science, **10.2**:115
18. Yuniarti S (2021). Relation between Knowledge and Mother's Occupation with Growth and Development of Children between Ages 5-6 in Tk At-Taqwa Cimahi. KnE Life Sciences, **1029-45**.

Descriptive Statistics

Statistic	Value
Sample Size	1023
Range	1200
Mean	801.51
Variance	91670.0
Std. Deviation	302.77
Coef. of Variation	0.37775
Std. Error	9.4662
Skewness	-0.02885
Excess Kurtosis	-1.0856

Percentile	Value
Min	200
5%	326.4
10%	392.4
25% (Q1)	547
50% (Median)	803
75% (Q3)	1059
90%	1212.6
95%	1266.8
Max	1400

Goodness of Fit - Summary

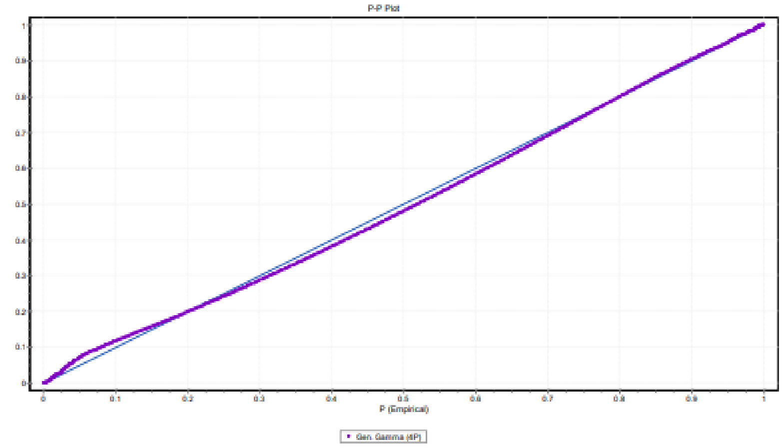
#	Distribution	olmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Chi-Squared	0.40107	25	6388.9	26	3136.3	25
2	Chi-Squared (2P)	0.05382	7	8.3089	7	47.297	6

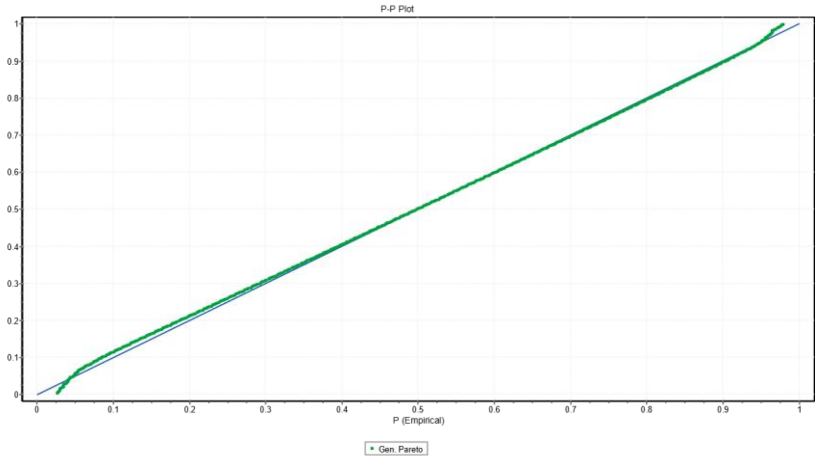
3	Dagum	0.15145	20	48.453	19	165.38	19
4	Dagum (4P)	0.55634	26	459.07	25	1332.7	24
5	Exponential	0.29126	22	171.28	22	779.34	22
6	Exponential (2P)	0.1897	21	97.085	20	311.88	20
7	Fatigue Life	0.08999	17	17.971	16	68.44	13
8	Fatigue Life (3P)	0.05583	10	8.505	8	48.822	8
9	Gamma	0.0784	15	15.99	13	84.478	17
10	Gamma (3P)	0.05999	12	8.8184	10	48.95	9
11	Gen. Extreme Value	0.04081	3	5.5434	2	29.522	2
12	Gen. Gamma	0.07316	13	11.9	12	55.082	12
13	Gen. Gamma (4P)	0.02259	1	1.1477	1	12.389	1
14	Gen. Pareto	0.02673	2	104.15	21	N/A	
15	Log-Gamma	0.09124	18	19.493	18	79.326	16
16	Log-Logistic	0.09521	19	18.625	17	76.928	15
17	Log-Logistic (3P)	0.05514	9	9.8907	11	52.19	11
18	Log-Pearson 3	0.0514	4	6.658	4	30.946	3
19	Logistic	0.0758	14	16.594	14	102.03	18
20	Lognormal	0.08422	16	16.655	15	69.104	14
21	Lognormal (3P)	0.05798	11	8.8022	9	49.921	10
22	Normal	0.05341	6	8.2789	6	47.701	7
23	Pareto	0.30941	24	203.86	24	675.72	21
24	Pareto 2	0.29133	23	171.4	23	788.71	23
25	Weibull	0.05164	5	6.4021	3	34.375	4
26	Weibull (3P)	0.05437	8	7.6801	5	43.558	5

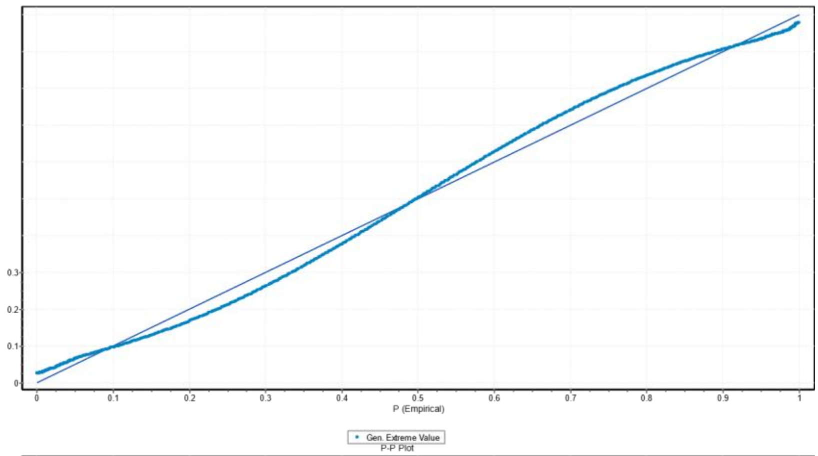
Fitting Results and PP plots and also QQ plots

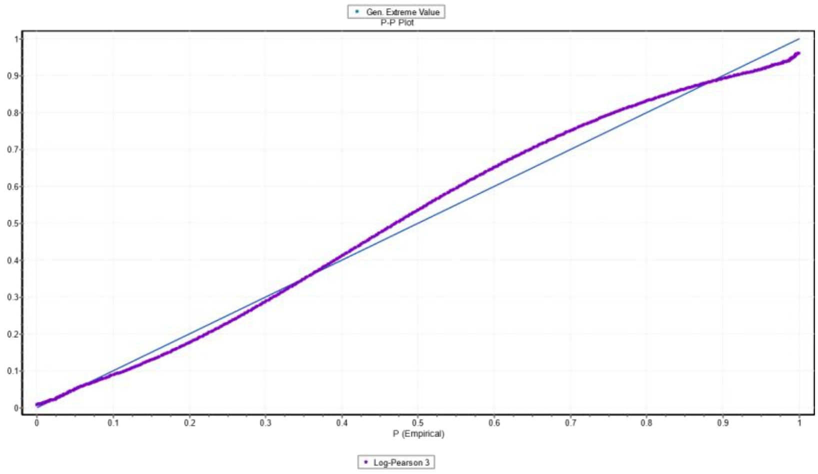
#	**Distribution**	**Parameters**
1	Chi-Squared	□=801

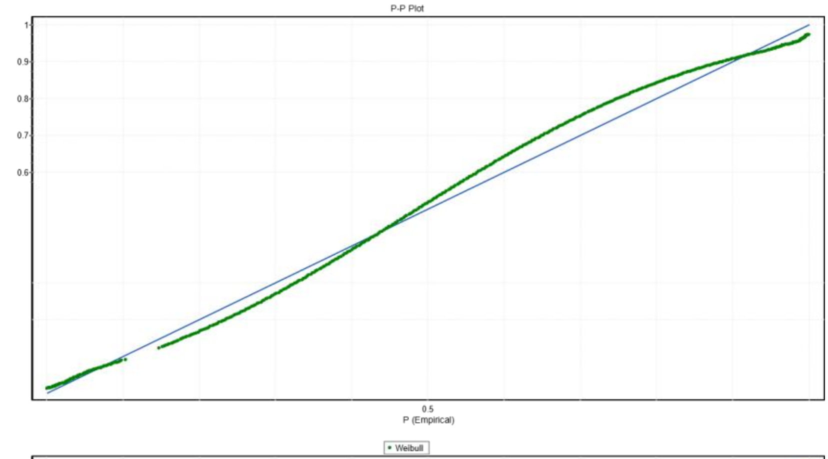
2	Chi-Squared (2P)	□=45804 □=-45003.0
3	Dagum	k=223.06 □=1.9705 □=35.667
4	Dagum (4P)	k=2.4908 □=0.27239 □=0.521 □=200.0
5	Exponential	□=0.00125
6	Exponential (2P)	□=0.00166 □=200
7	Fatigue Life	□=0.44622 □=728.47
8	Fatigue Life (3P)	□=0.01482 □=20369.0 □=-19571.0
9	Gamma	□=7.0078 □=114.37
10	Gamma (3P)	□=55.569 □=40.833 □=-1468.4
11	Gen. Extreme Value	k=-0.29662 □=310.56 □=694.7
12	Gen. Gamma	k=0.96554 □=6.5283 □=114.37
13	Gen. Gamma (4P)	k=16.641 □=0.07515 □=1124.4 □=198.57
14	Gen. Pareto	k=-1.0287 □=1073.6 □=272.31
15	Log-Gamma	□=228.54 □=0.02888
16	Log-Logistic	□=3.9483 □=735.54
17	Log-Logistic (3P)	□=3.9682E+8 □=7.2523E+10 □=-7.2523E+10
18	Log-Pearson 3	□=7.7284 □=-0.15707 □=7.8152
19	Logistic	□=166.93 □=801.51
20	Lognormal	□=0.43645 □=6.6012
21	Lognormal (3P)	□=0.05254 □=8.6547 □=-4943.7
22	Normal	□=302.77 □=801.51
23	Pareto	□=0.76751 □=200
24	Pareto 2	□=91.812 □=73394.0
25	Weibull	□=2.8739 □=898.33
26	Weibull (3P)	□=2.7999 □=859.49 □=37.961

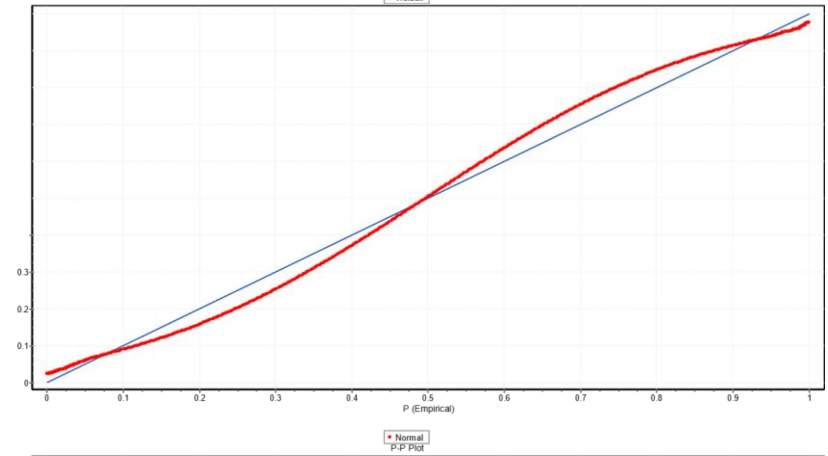

P-P Plot
P (Empirical)
Gen. Gamma (4P)

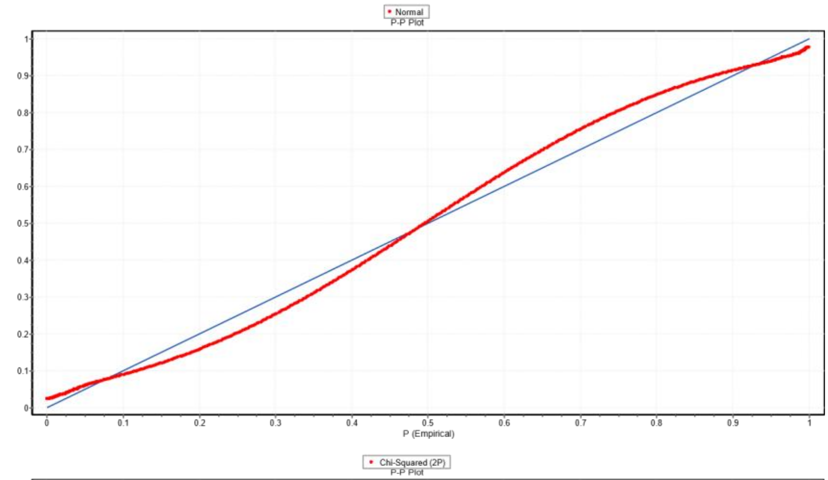

P-P Plot
P (Empirical)
Gen. Pareto

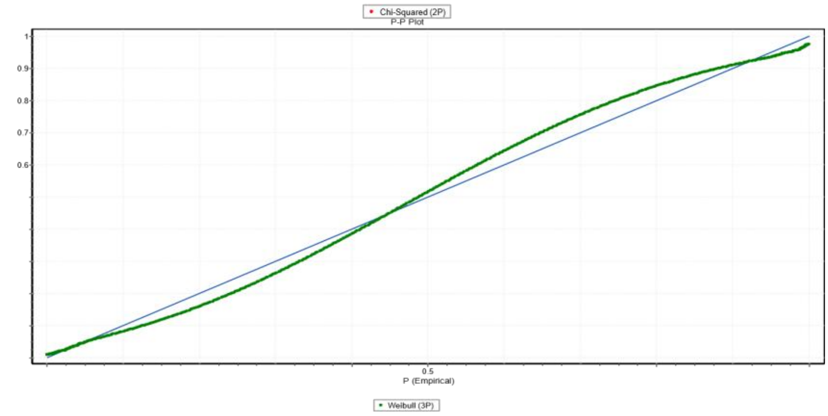

P (Empirical)
Gen. Extreme Value

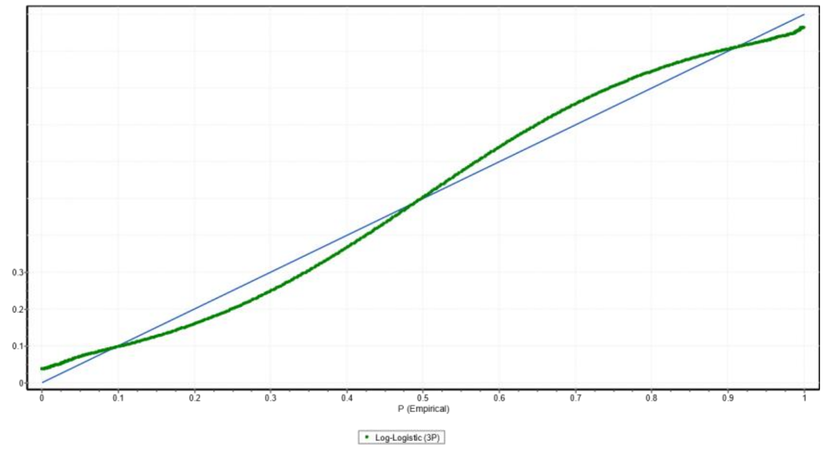

P-P Plot
P (Empirical)
Log-Pearson 3

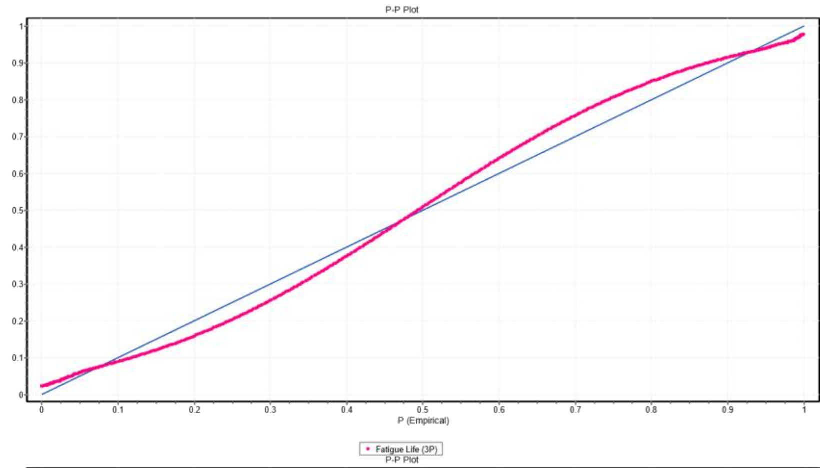

P-P Plot
1
0.9
0.8
0.7
0.6
0.5
P (Empirical)
Weibull

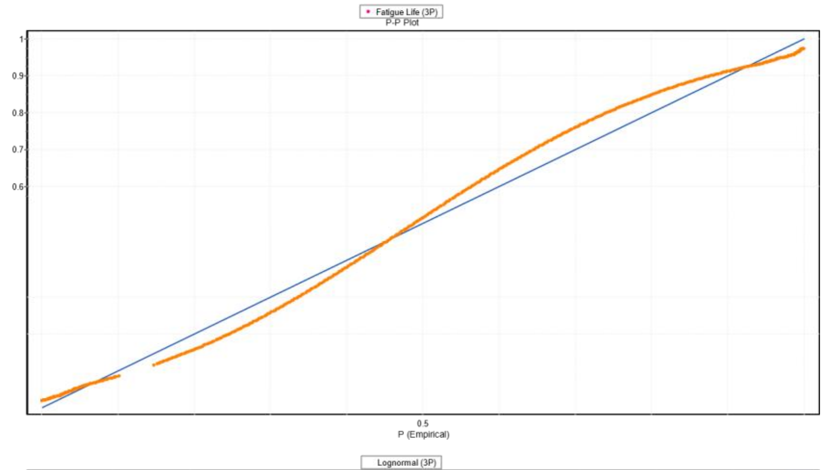

0.3
0.2
0.1
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
P (Empirical)
Normal

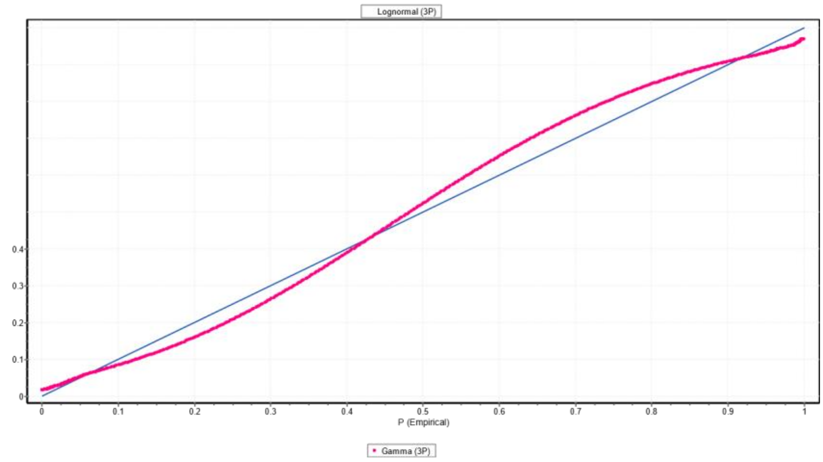

P-P Plot
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
P (Empirical)
Chi-Squared (2P)

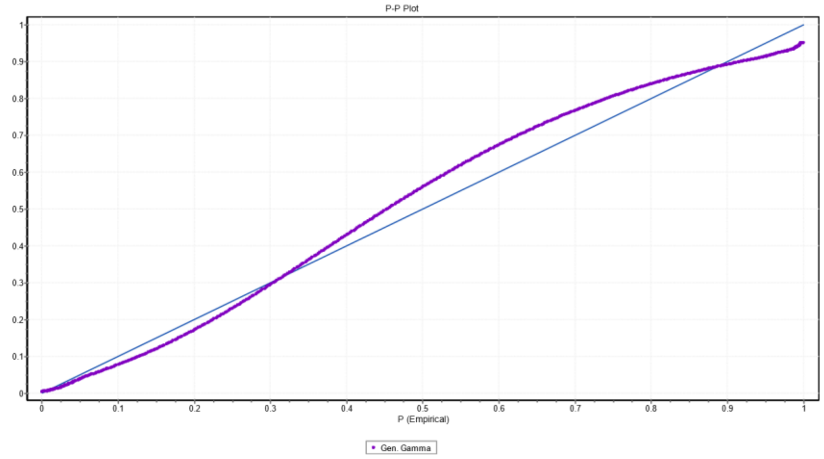

P-P Plot
1
0.9
0.8
0.7
0.6
0.5
P (Empirical)
Weibull (3P)


P (Empirical)
Log-Logistic (3P)

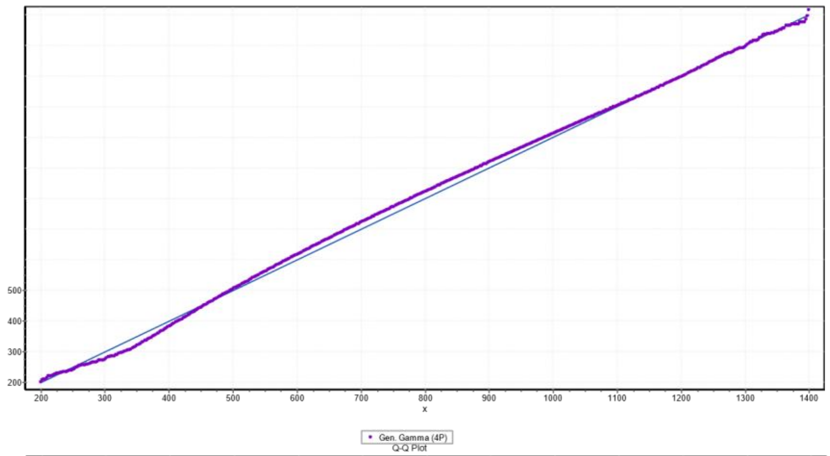

P-P Plot
P (Empirical)
Fatigue Life (3P)

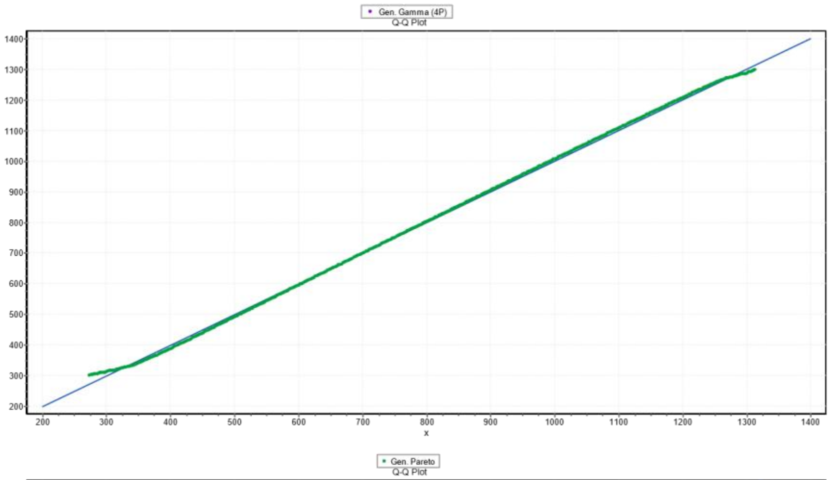

P-P Plot
P (Empirical)
Lognormal (3P)

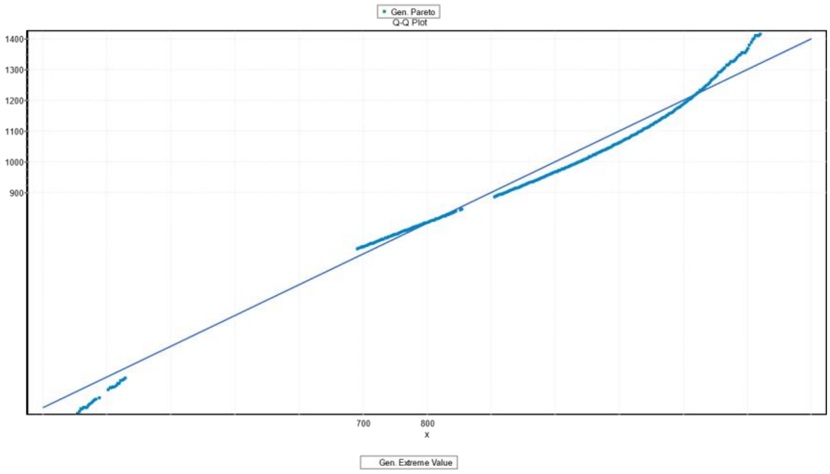

P (Empirical)
Gamma (3P)

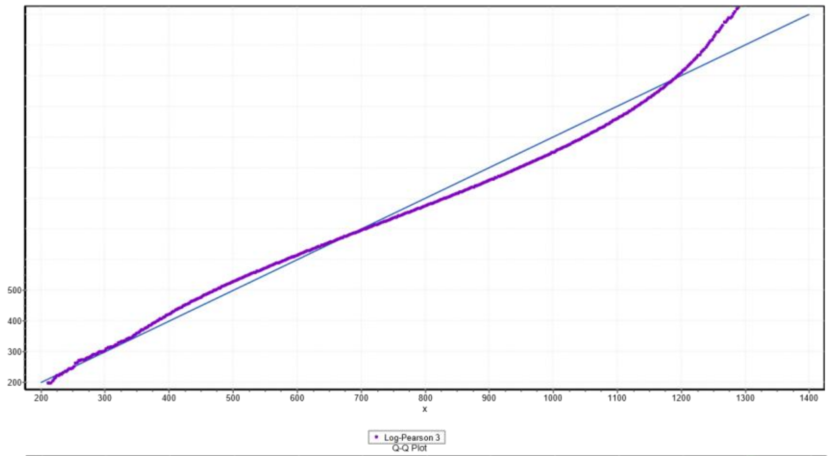

P-P Plot
P (Empirical)
Gen. Gamma

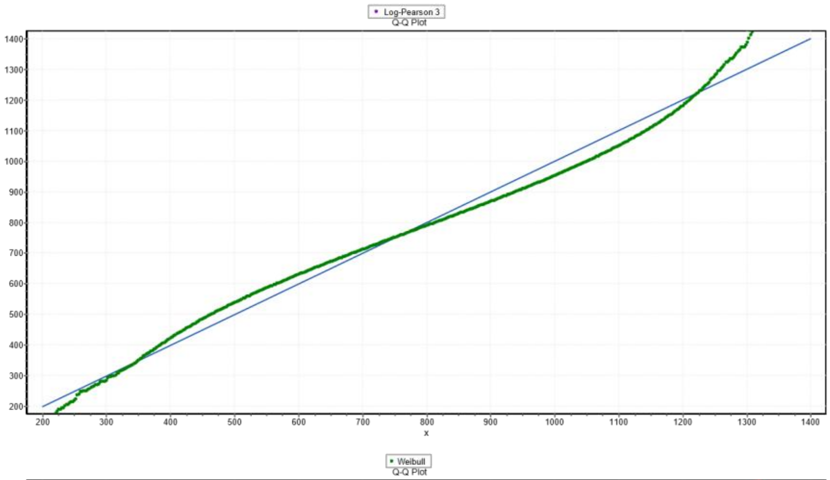
Q Q Plots

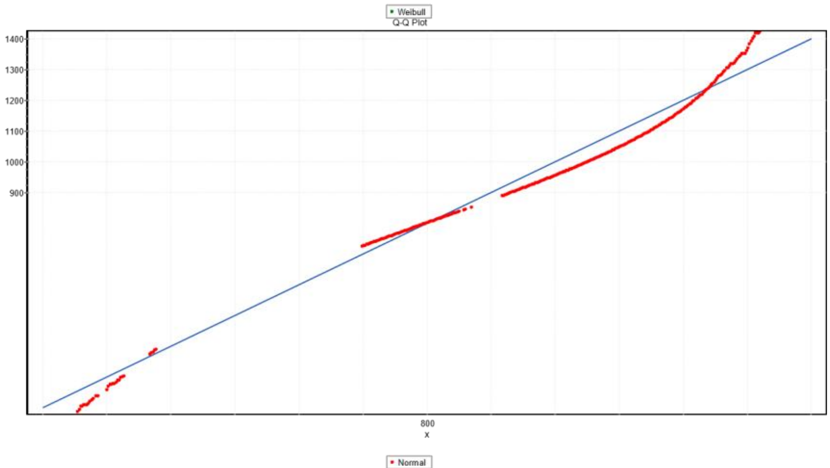

x
Gen. Gamma (4P)

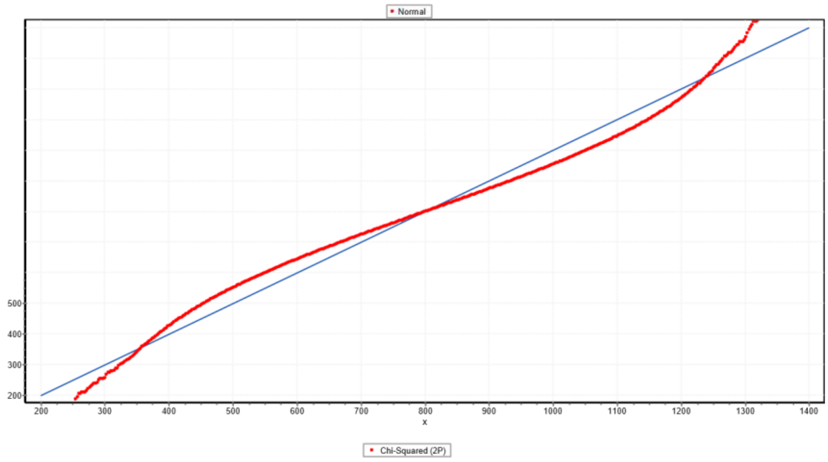

Q-Q Plot
x
Gen. Pareto

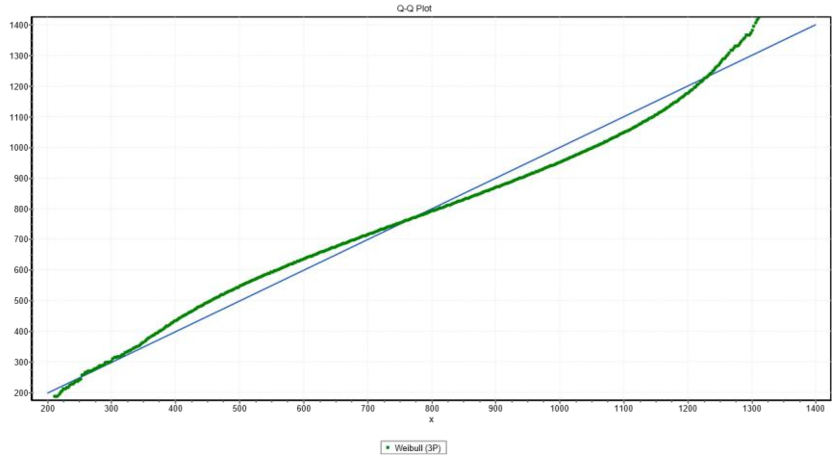

Q-Q Plot
x
Gen. Extreme Value

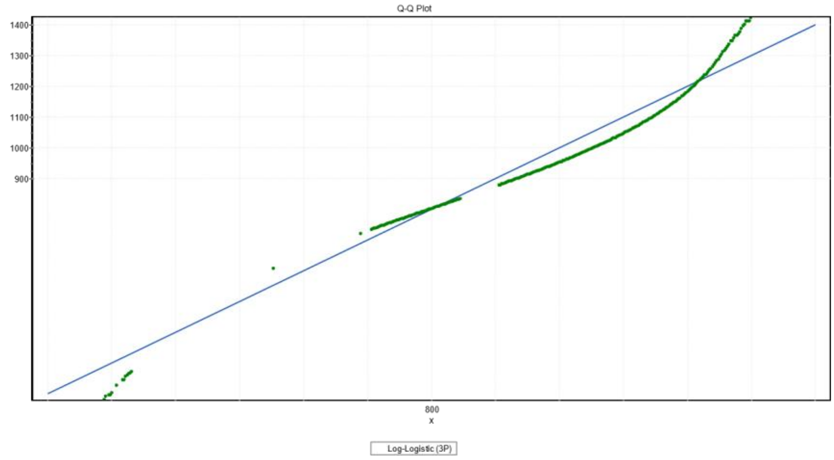

x
Log-Pearson 3

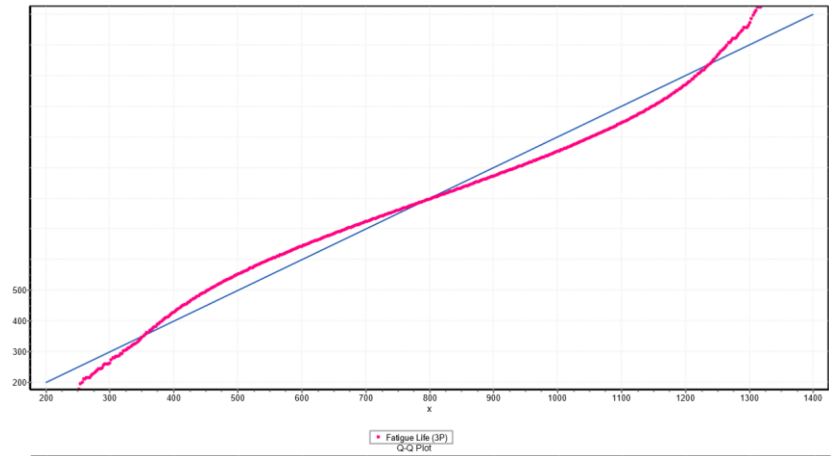

Q-Q Plot
x
Weibull

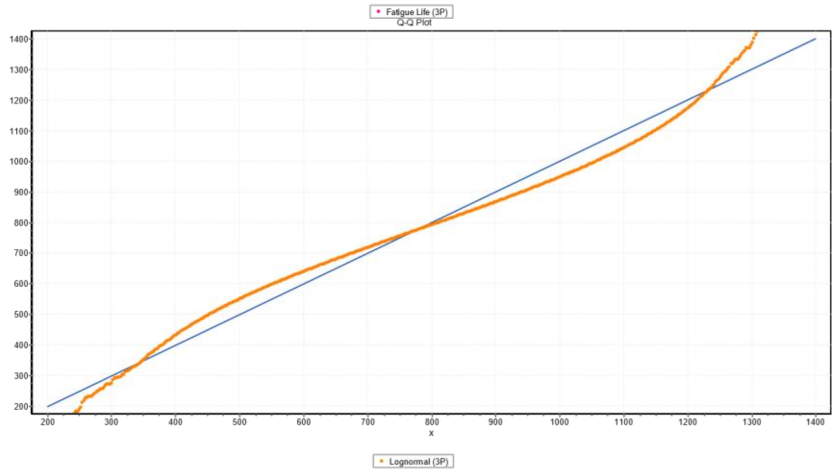

Q-Q Plot
x
Normal

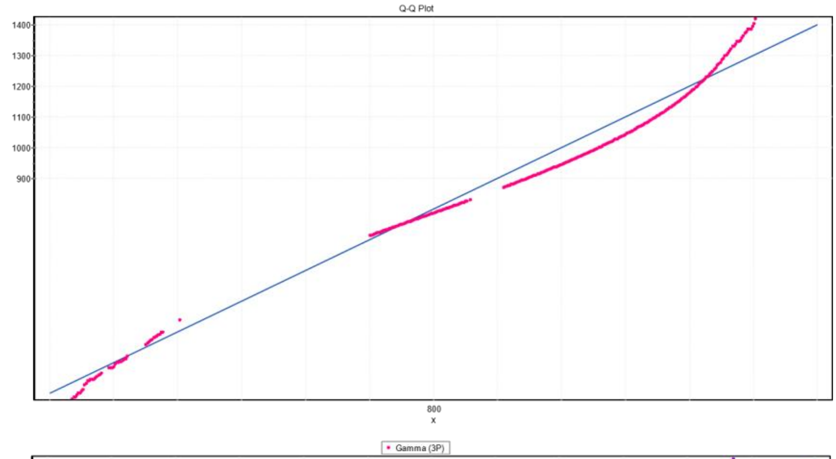

x
Chi-Squared (2P)

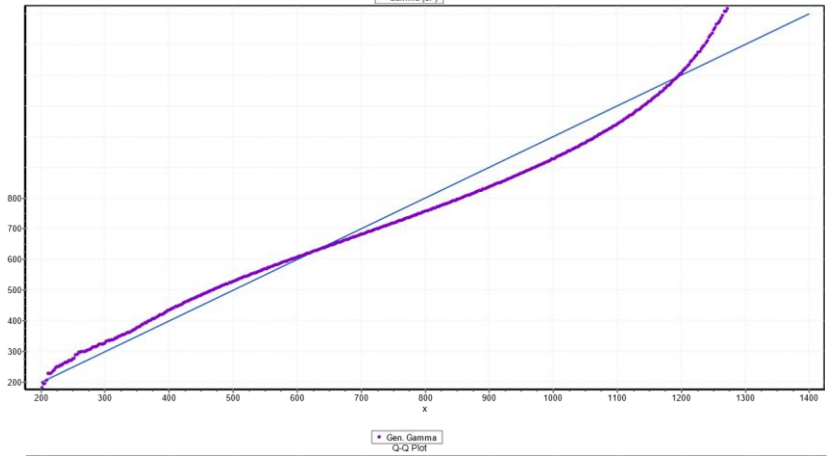

Q-Q Plot
1400
1300
1200
1100
1000
900
800
700
600
500
400
300
200
200 300 400 500 600 700 800 900 1000 1100 1200 1300 1400
x
Weibull (3P)

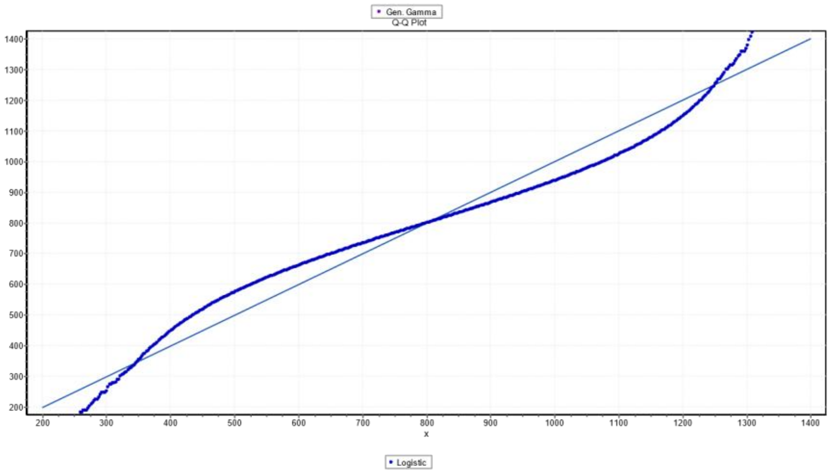

Q-Q Plot
1400
1300
1200
1100
1000
900
800
x
Log-Logistic (3P)

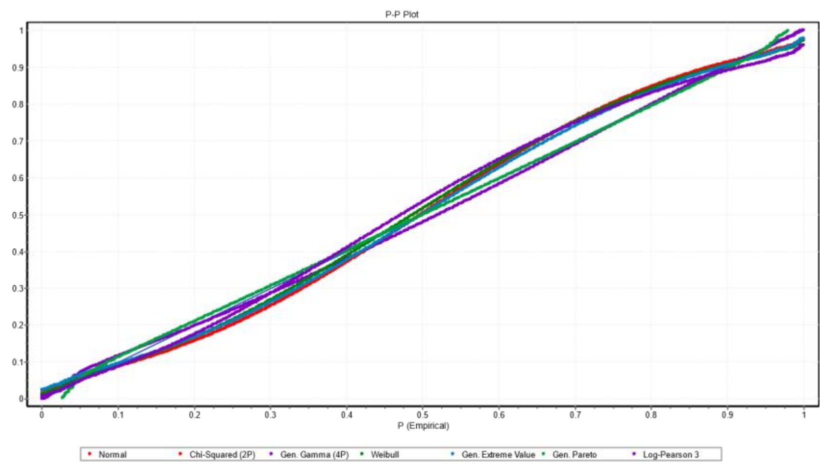

500
400
300
200
200 300 400 500 600 700 800 900 1000 1100 1200 1300 1400
x
Fatigue Life (3P)

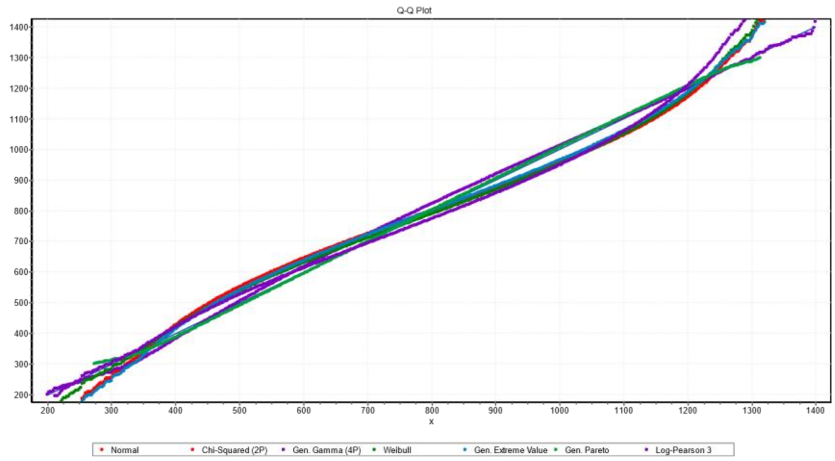

Q-Q Plot
1400
1300
1200
1100
1000
900
800
700
600
500
400
300
200
200 300 400 500 600 700 800 900 1000 1100 1200 1300 1400
x
Lognormal (3P)

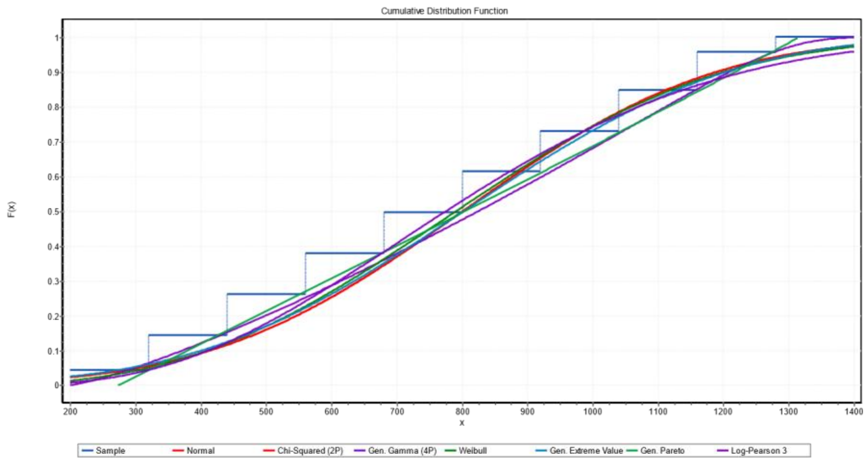

Q-Q Plot
x
Gamma (3P)

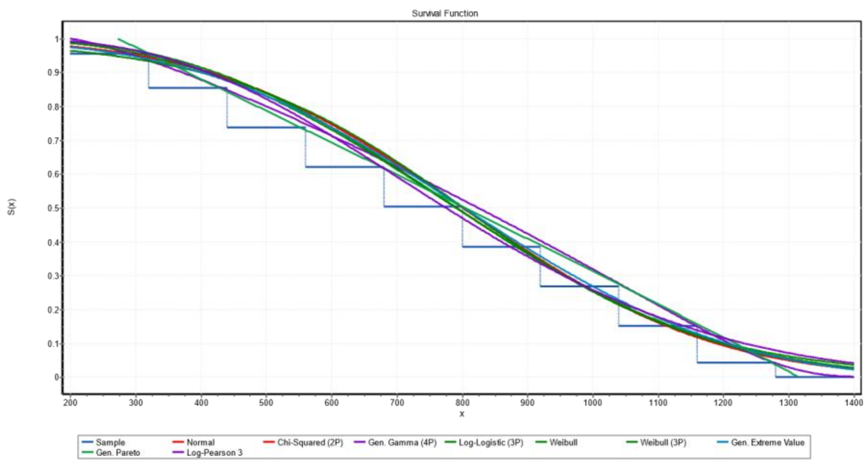

x
Gen. Gamma

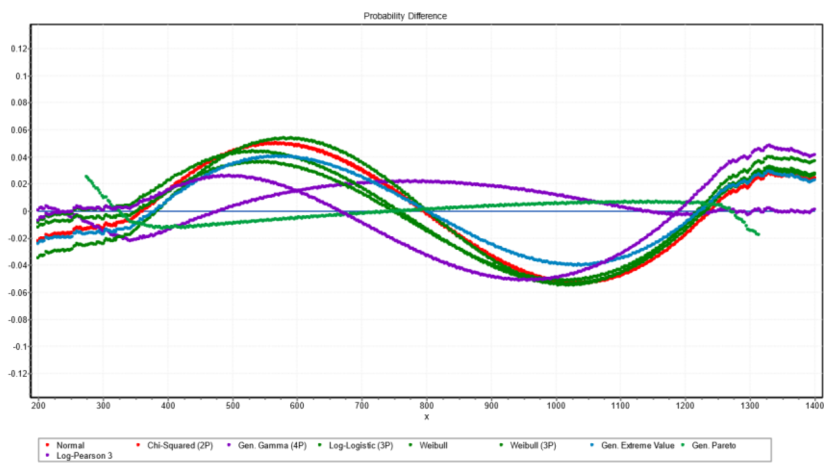

Q-Q Plot
x
Logistic

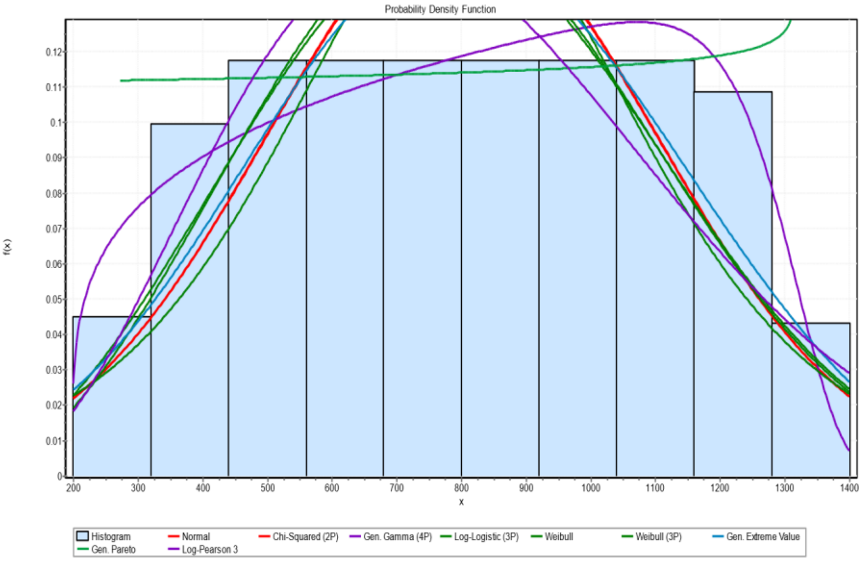

P-P Plot
P (Empirical)
Normal
Chi-Squared (2P)
Gen. Gamma (4P)
Weibull
Gen. Extreme Value
Gen. Pareto
Log-Pearson 3


Q-Q Plot
x
Normal
Chi-Squared (2P)
Gen. Gamma (4P)
Weibull
Gen. Extreme Value
Gen. Pareto
Log-Pearson 3


Cumulative Distribution Function
F(x)
x
Sample
Normal
Chi-Squared (2P)
Gen. Gamma (4P)
Weibull
Gen. Extreme Value
Gen. Pareto
Log-Pearson 3


Survival Function
S(x)
x
Sample
Normal
Chi-Squared (2P)
Gen. Gamma (4P)
Log-Logistic (3P)
Weibull
Weibull (3P)
Gen. Extreme Value
Gen. Pareto
Log-Pearson 3


Probability Difference
x
Normal
Chi-Squared (2P)
Gen. Gamma (4P)
Log-Logistic (3P)
Weibull
Weibull (3P)
Gen. Extreme Value
Gen. Pareto
Log-Pearson 3


Probability Density Function
f(x)
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
0.11
0.12
200
300
400
500
600
700
800
900
1000
1100
1200
1300
1400
x
Histogram
Normal
Chi-Squared (2P)
Gen. Gamma (4P)
Log-Logistic (3P)
Weibull
Weibull (3P)
Gen. Extreme Value
Gen. Pareto
Log-Pearson 3