

Effectiveness of log-logistic distribution to model water-consumption data

Seevali Surendran^{1,2*} and Kiran Tota-Maharaj¹

¹Faculty of Environment and Technology, University of the West of England, Bristol (UWE Bristol), Bristol, BS16 1QY, UK; ²Environment Agency, Kings Meadow House, Kings Meadow Road, Reading, RG1 8DQ, UK. *Corresponding author Email: seevali.surendran@environment-agency.gov.uk

ABSTRACT

Water consumption varies with time of use, season and socio-economic status of consumers, and is defined as a continuous random variable. Incorporating probabilistic nature in water-consumption modelling will lead to more realistic assessments of performance of water distribution systems. Furthermore, fitting water-consumption patterns into a suitable statistical distribution will assist in determining how often peaks will occur, or the probability of exceeding the peaking factor in a system, for incorporation into design calculations. There are few studies in the literature where the random variations of consumption have been considered. The purpose of this study is to evaluate real water-consumption data from the United Kingdom (UK) and North America and to investigate the possibility of establishing a standard probability distribution function to apply in simulating water consumption in developed countries. Daily water-consumption data for five years (2009–2013) were obtained from water companies in the UK and North America and analysed by fitting into normal, log-normal, log-logistic and Weibull distributions. Statistical modelling was performed using MINITAB version 18 statistical package. The Anderson-Darling goodness-of-fit test was used to show how well the selected statistical distribution fits the water-consumption data.

KEYWORDS | Anderson-Darling statistical test, log logistic distribution, MINITAB, probability distribution function, random nature, water demand

30 INTRODUCTION

31 A major unresolved problem in water-consumption modelling is the identification of an
32 appropriate statistical distribution which best represents the water-consumption pattern. Fitting
33 water-consumption patterns into a suitable statistical distribution will assist in finding how often
34 the peaks will occur, or the probability of exceeding the peaking factor, in the system to
35 incorporate into design calculations with a scientifically proven method. The aim of this research
36 is to study real water-consumption data and to find a standard statistical distribution to use in
37 water-consumption modelling to address the probabilistic nature of water consumption. The
38 advantage of modelling real water-consumption data is that it will permit forecasting of the
39 probability of occurrence in any consumption value and provide confidence in future projections.
40 There are relatively few studies that have considered the random variations of water
41 consumption. It is often assumed that variation in water consumption in distribution systems
42 follows the normal distribution, usually with insufficient justification. Furthermore, there is
43 inadequate reliable data regarding the suitability of various statistical distributions for modelling
44 water consumption. Goulter and Bouchart (1990), Bao and Mays (1990), Xu and Goulter (1997,
45 1998, 1999), Syntetos et al. (2001, 2005) and Kwietniewski (2003) made assumptions that water
46 consumption has a normal distribution. Mays (1994) used randomly generated water-
47 consumption data using a range of distributions to study the sensitivity of a system's
48 performance to changes in water-consumption patterns. Khomsi et al. (1996) stated that the
49 consumption of water has a normal distribution based on the Kolmogorov-Smirnov test (KS).
50 However, the KS test is more sensitive near the centre of the distribution than at the tails and was
51 not suitable to validate the water-consumption data, as the high consumption data points lie on
52 the tail of the distribution. In the technical literature further research papers written by De
53 Marinis et al. (2007); Tricarico et al. (2007) and Gato-Trinidad and Gan (2012) support the
54 effectiveness of the normal distribution by means of rigorous statistical inferences on real data.
55 The American Water Works Association (AWWA) Research Foundation sponsored a study
56 (Bowen et al., 1993) in residential water-use patterns in the USA, and results revealed that the
57 demand data was not distributed normally. Several data transformations to improve the data
58 analysis were investigated and it was found that the log transformation was only mildly effective
59 in reducing the positive skewness of the frequency distributions of the data.

60 Surendran and Tanyimboh (2004), and Tanyimboh et al. (2004) addressed the issue of the
61 modelling of short-term consumption variations in a comprehensive way, using UK water-
62 consumption data and concluded that data fitted better with a long tail distribution rather than a
63 normal distribution. However, the findings were limited to UK water-consumption data.

64 The log-logistic distribution resembles the log-normal in shape, it has a more tractable
65 form and is one of the few distributions for which the probability distribution, cumulative density
66 and quartile functions exist in simple closed form (Kleiber, 2004). Furthermore, it can cope well
67 with outliers in the upper tail (Dey & Kundu 2004). The log logistic distribution has been used
68 by Swamee (2002), El-Saidi et al. (1990) and Rowinski et al. (2001), in hydrological studies
69 (frequency analysis of multi-year drought durations, precipitation data and flood frequency
70 analysis) and survival (reliability) analysis, which have the outliers in upper tail. Gargano et al.
71 (2016, 2017) stated that log-logistic distribution is the best fit for real water-consumption data.

72

73 Ashkar and Mahdi (2006), Cordeiro et al. (2012) and Ramos et al. (2013) described the
 74 log-logistic distribution in detail and concluded that the log-logistic model is suitable for positive
 75 skewed data and positive random variables. As water consumption is a random variable and is
 76 positively skewed, it defines the suitability of log-logistic distribution in modelling water
 77 consumption.

78

79 **Identifying a suitable statistical distribution**

80 It is a general assumption that water consumption follows a normal distribution and literature
 81 review shows that the studies undertaken in the past supported this assumption. Water
 82 consumption will vary as a result of weather patterns, fire incidents and leakages, and these
 83 scenarios will lead to extreme usage conditions. Consequently, due to high consumption from
 84 time to time, the data would fit better in a positively skewed distribution than in a normal
 85 distribution

86 As a preliminary check, to identify the distribution patterns of the real water-consumption
 87 data obtained from the two water companies, normal graphs were drawn to check the normality
 88 of the data. The normal graphs were drawn for the 20 data sets (yearly data) and they show that
 89 out of 20 data sets, 2 sets follow a normal distribution and the other 18 sets follow a positively
 90 skewed distribution.

91 It can be concluded that water-consumption data will fit well into positively skewed distributions
 92 such as log-normal, log-logistic and Weibull distributions.

93 This study used these distributions to select the best fit for water-consumption modelling.
 94 The normal distribution was used for comparison. These four distributions are described in Table
 95 1, providing their suitability on application to modelling water consumption.

96

97

98 Table 1. Suitability for using normal, log-normal, log-logistic and Weibull distributions in
 99 modelling

Distribution	Description	Suitability for water-consumption data modelling	Probability distribution function (PDF)
Normal	Has the familiar symmetrical bell shape and its sample space extends from minus to plus infinity.	The water-consumption data contains only positive values and since the data typically show skewed frequency patterns, the	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right] \quad -\infty < x < \infty$ <p>where, μ is mean of the distribution and σ is</p>

		normal distribution must be approached with caution, particularly if inferences will focus on the tails of the distribution.	the standard deviation.
Log-normal	Logarithmically related to normal distribution and shows considerable flexibility of shape, which is always skewed to the right.	In log-normal distribution its sample space admits only positive values and suitable to use in analysing water-consumption data.	$f(x) = \frac{1}{\sigma x \sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}(\ln x - \mu)^2\right] \quad x, \mu, \sigma > 0$ <p>where μ is the mean and σ is the standard deviation.</p>
Log-logistic	The log-logistic distribution resembles the log-normal in shape, has a more tractable form. It can cope well with outliers in the upper tail.	It is a uni-model, defined only for positive random variables and positively skewed which is best representing the water consumption pattern.	$f(t) = \frac{\lambda K (\lambda t)^{K-1}}{[1 + (\lambda t)^K]^2} \quad t \geq 0$ <p>where K is called a shape parameter, as K increases the density become more peaked. The parameter λ is a scale parameter.</p>
Weibull	Depending on the values of the parameters, the Weibull distribution can be used to model a variety of life behaviors and provides better distribution for life length data.	To use Weibull distribution in analysis, it is essential to have a very good justifiable estimate for the shape parameter to replicate the accurate distribution pattern.	$f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} \exp\left[-\left(\frac{t}{\eta}\right)^\beta\right]$ <p>where β is the shape parameter and η is the scale parameter.</p>

100

101 **Description of data and the relative water distribution systems**

102 The daily water-consumption data for the five years from 1st April 2009 to 1st April 2013 were
103 obtained from a water utility company in North West Region of England to use in this research.

104 The water works system delivers water to approximately 6.7 million households and businesses
105 in the UK. The data were collected at the supply end of the network system using flow meters
106 which are either connected to telemetry (which are live) or data loggers. The data loggers record
107 the number of pulses within a 15-minute interval. This was then used to calculate and average

108 the flow rate during the 15-minute period, depending on the pulse setting (i.e. how many litres
109 per pulse). This raw data is imported daily into the data management system and converged to
110 hourly and daily volumes.

111 To analyse the North American daily water consumption, data for three demand zones
112 from a Canadian city in Manitoba Province were obtained. The data were collected using flow
113 meters connected to data loggers at the water treatment plant by the water services division. The
114 data were received between 1st January 2009 and 31st December 2014. The water supply system
115 delivers an average of 225 million liters per day of water to approximately 270,000 households
116 and businesses across approximately 297 square kilometers (114 square miles) of developed area
117 in Canada.

118

119 **METHODOLOGY**

120 In this research, a suitable statistical distribution was selected using a descriptive analysis. Data
121 were screened and sorted by plotting raw demand data against time. This provided a quick
122 reference to check the abnormality of data. If the points were homogeneously distributed and
123 there were no negative points, this meant that the data were all most acceptable to use in the
124 analysis. Similarly, if there were any inconsistencies in the distribution, these time series graphs
125 would show the abnormal data points to be removed prior to analysis.

126 The data were then analysed using MINITAB version 18 statistical package, and was
127 fitted into a suitable probability distribution. As previously described, the descriptive analysis
128 show that data fit well into a positively skewed distribution and log-normal, Weibull and log-
129 logistic distributions were applied to find an appropriate distribution. The normal distribution
130 was used for comparison purposes.

131

132 **Analysing data**

133 Once data has been fitted in to any distribution, the ‘goodness-of-fit test’ should be used to see
134 how well the data fit into the distribution. The parameters of distribution such as location, shape
135 and scale are also essential to describe the distribution.

136

137 *The Anderson-Darling test*

138 The appropriateness of the distribution for water-consumption data was assessed by comparison
139 to the normal, log-normal, log-logistic and Weibull distributions using the Anderson-Darling
140 goodness of fit test. The Anderson-Darling Test (Stephens, 1974) is used to test if a sample of
141 data came from a population with a specific distribution. It is a modification of the K-S test and
142 gives more weight to the tails than the K-S test. The K-S test is distribution free in the sense that
143 the critical values do not depend on the specific distribution being tested. The Anderson-Darling
144 Test makes use of the specific distribution in calculating critical values. This has an advantage of
145 allowing a more sensitive test and the disadvantage is that critical values must be calculated for
146 each distribution. The critical values were calculated, tabulated and published by Stephens
147 (1974), for a few specific distributions, including log-logistic distribution.

148 The equation for the Anderson-Darling parameter, A^2 , is

149

$$150 \quad A^2 = -n - \frac{1}{n} \sum_{i=1}^n (2i - 1) [\ln \omega_i + \ln(1 - \omega_{n+1-i})]$$

151 where, n is the number of observations and ω_i is the value of the distribution in question at the i th
152 largest observation. A smaller AD value indicates that the distribution fits the data better. The
153 critical value of the Anderson-Darling parameter at the 95% confidence interval is 2.492 the 1%
154 point is 3.857 for $n \geq 5$ (Johnson, 2000). The Anderson-Darling test was preferred to the
155 Kolmogorov-Smirnov test because of the latter's lack of sensitivity in tails (Ahmad et al., 1988;
156 Johnson, 2000).

157

158 *Parameter estimates*

159 The location and scale parameters are associated with central tendency and dispersion,
160 respectively, and are essential to describe the distribution. The parameters for normal distribution
161 are the mean and standard deviation and they are directly related to the location and scale
162 parameters (Rigby, 2004). The log-normal, log-logistic and Weibull distributions use location,
163 shape or scale as their parameters and unlike normal distribution they need to transform the
164 location and scale parameters to represent mean and standard deviation using complex equations.
165 These parameters have allowed the distribution to have flexibility and effectiveness in modelling
166 applications. In simple terms the shape parameter allows a distribution to take on a variety of
167 shapes depending on the value of the shape parameter. The effect of the location parameter is to

168 shift the graph to the left or right of the horizontal axis. The scale parameter describes the
169 stretching capacity of the probability distribution function.

170

171 *The graphical method*

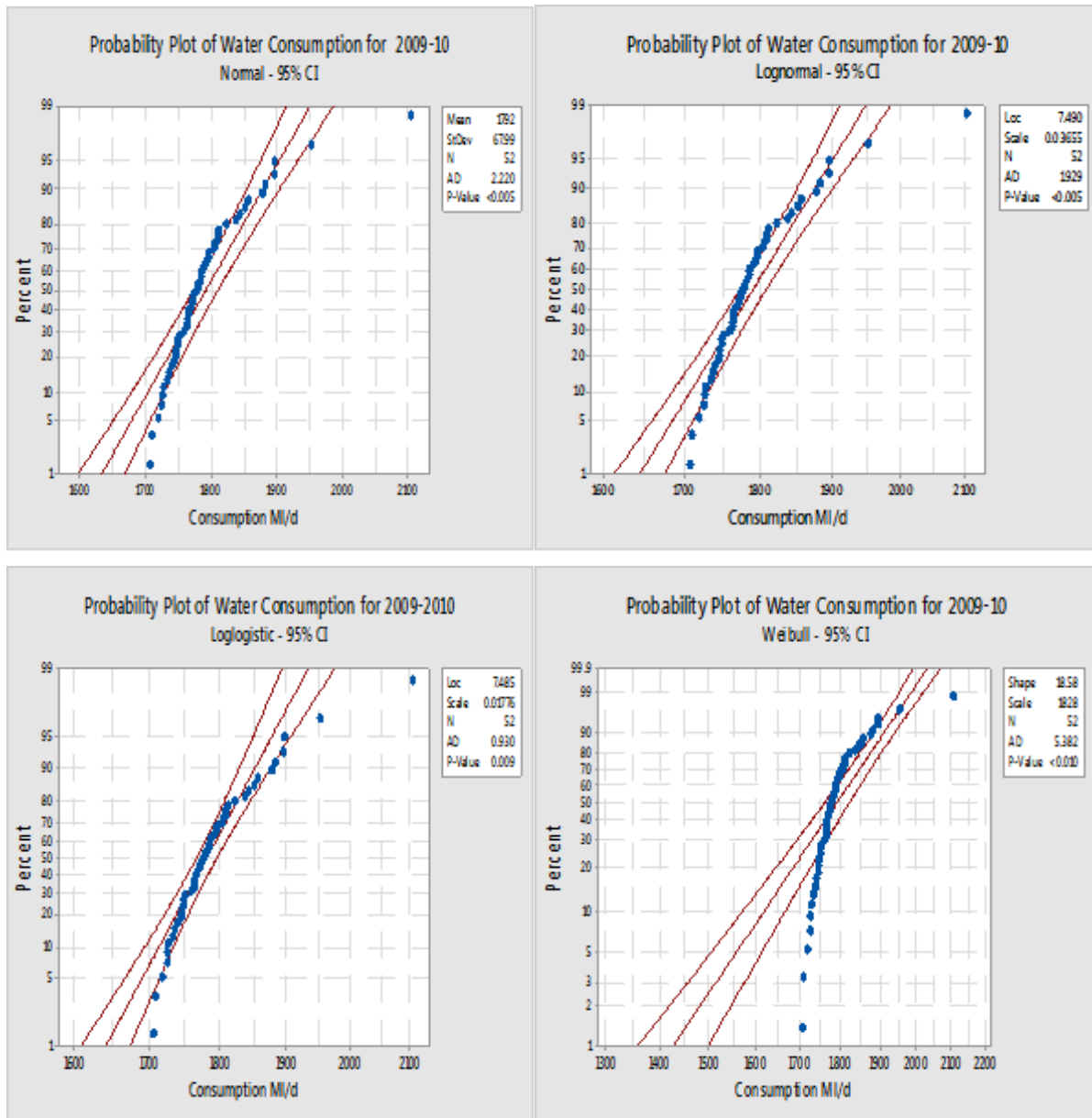
172 There are various numerical and graphical methods used in the literature for estimating the
173 parameters of a probability distribution. In this study, graphical methods were selected for the
174 analysis along with the maximum likelihood method to draw the probability plots (see Figures 1
175 and 2 in the following section). The data were analysed using 95% confidence intervals (5%
176 significance level) and were fitted to normal, log-normal, Weibull and log-logistic distributions
177 to establish the parameters for the distribution. The middle line in the probability plot shows the
178 normal line and the other two lines show the 95% confidence intervals. Montgomery and Runger
179 (2002) stated that normal probability plots are useful in identifying distributions that fit into the
180 normal distribution and those which have skewed distributions with long tails. If the data falls
181 below the normal line then data has a positively skewed distribution (Montgomery & Runger,
182 2002).

183

184

185 **RESULTS AND DISCUSSION**

186 The normal probability plots for the UK and North American water-consumption data for the
187 year 2009 is shown in Figure 1 and Figure 2, respectively. The data shown in Figure 1 and Figure
188 2 shows that values on both ends tend to fall below the normal line. This demonstrates that the
189 data has a positively skewed distribution. Further to this, the graphs of four distributions for the
190 UK and North American data show that more data points are within the 95% confidence level for
191 log-logistic distribution than log-normal, Weibull and normal distributions.



192

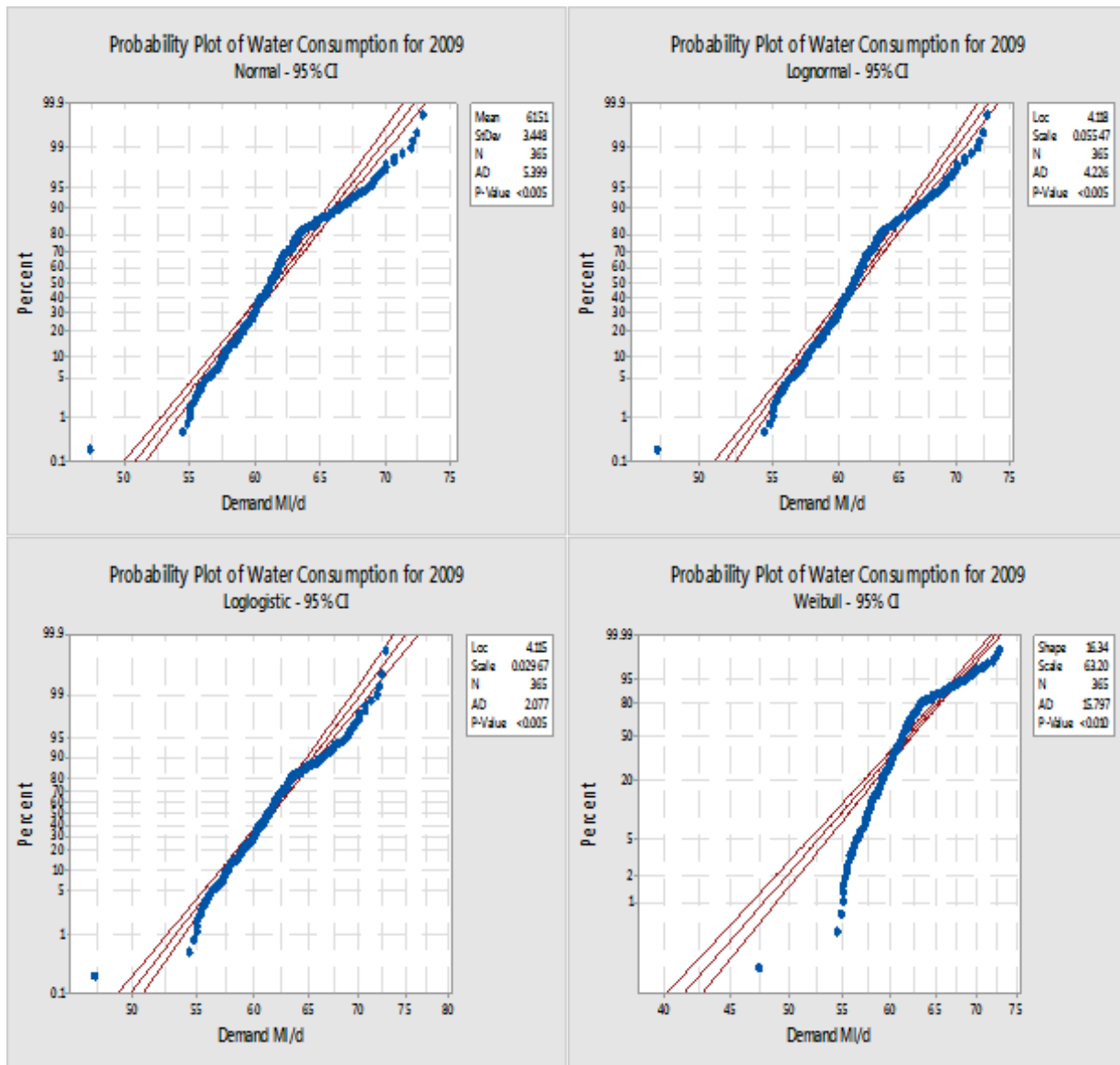
193

194

195

196

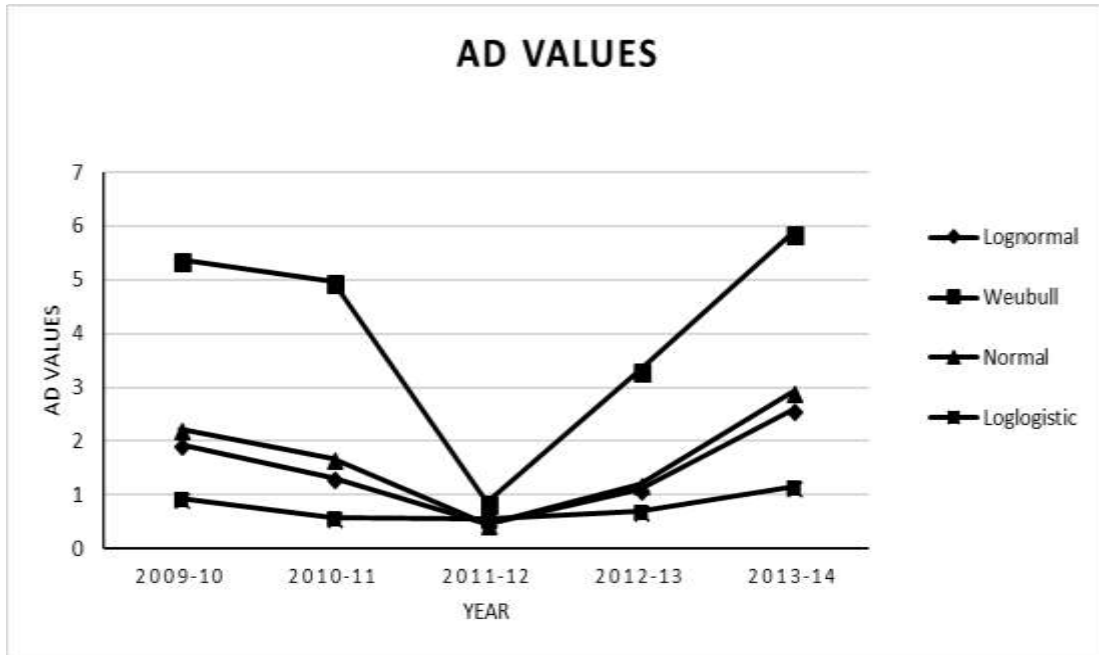
Figure 1. Probability plots for normal, log-normal, log-logistic and Weibull – UK



197
 198 Figure 2. Probability plots for normal, log-normal, log-logistic and Weibull – North American
 199 data.

200
 201
 202 **The goodness-of-fit test**

203 The Anderson-Darling (AD) goodness-of-fit test was used to confirm the best fit of data for
 204 normal, log-normal, log-logistic and Weibull distribution. The AD values for normal, log-
 205 normal, log-logistic and Weibull distributions for the UK and North American data are shown in
 206 Figures 3 to 6. The data used in this study has shown that the log-logistic distribution has the
 207 lowest AD values when compared with the normal, Weibull and log-normal distributions.

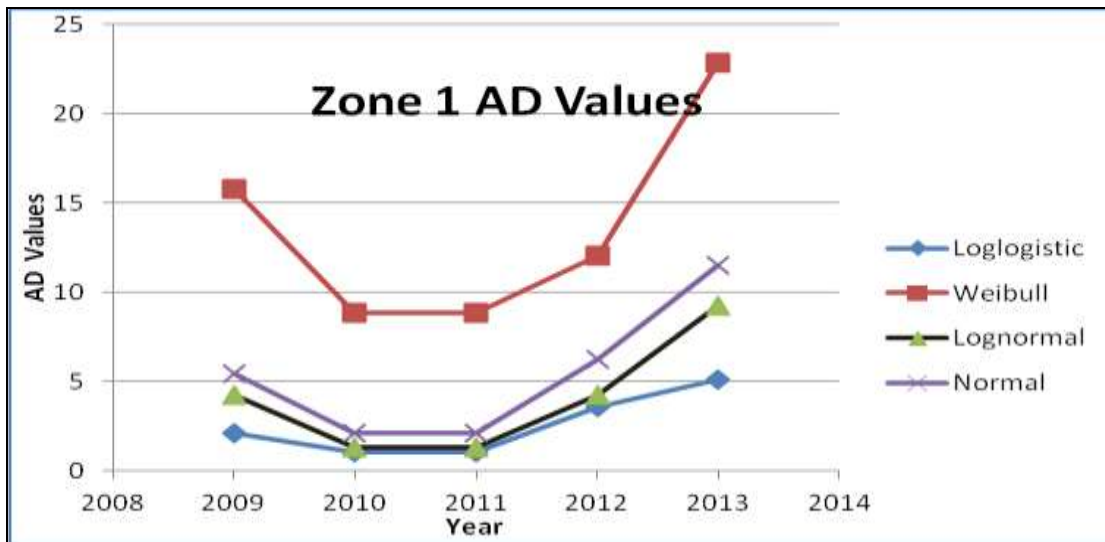


208

209

Figure 3. Anderson-Darling (AD) test values – UK.

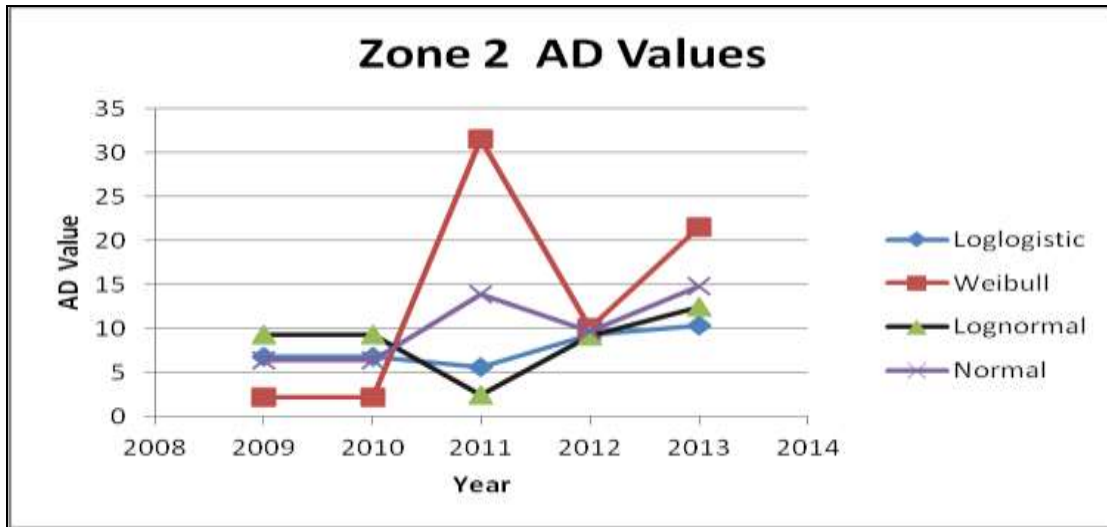
210



211

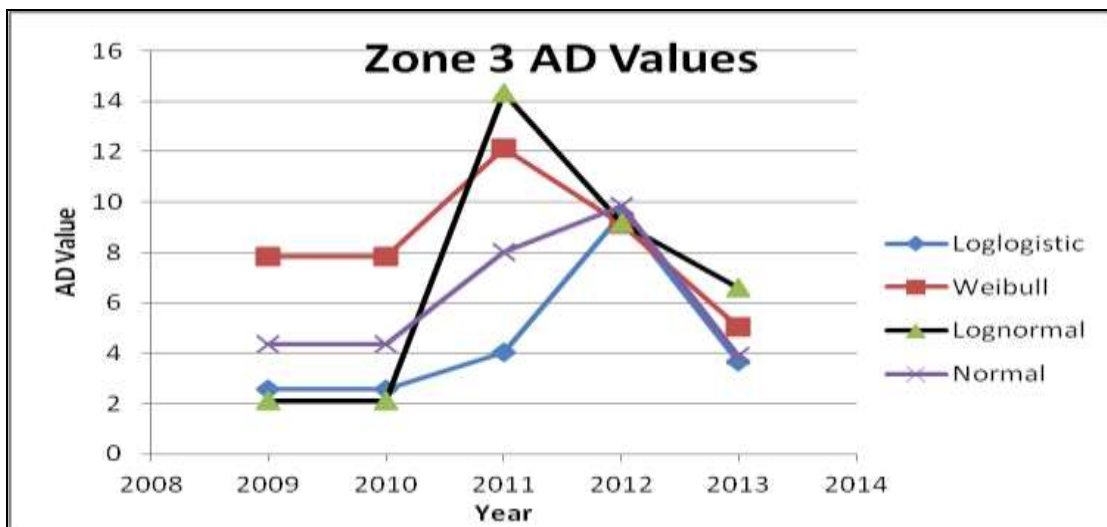
212

Figure 4. Anderson-Darling (AD) test values for Zone 1 – North America.



213
214
215
216

Figure 5. Anderson-Darling (AD) test values for Zone 2 – North America.



217
218
219
220

Figure 6. Anderson-Darling (AD) test values for Zone 3 – North America.

221 Parameter estimates

222 The location and scale parameters are associated with central tendency and dispersion,
223 respectively, and are essential to describe the distribution. The parameters for normal
224 distribution are the mean and standard deviation and they are directly related to the location and
225 scale parameters (Rigby, 2004). The log-normal, log-logistic and Weibull distributions use
226 location, shape or scale as their parameters and unlike normal distribution they need to transform

227 the location and scale parameters to represent mean and standard deviation using complex
 228 equations.

229 These parameters have allowed the distribution to have flexibility and effectiveness in
 230 modelling applications. In simple terms the shape parameter allows a distribution to take on a
 231 variety of shapes depending on the value of the shape parameter. The effect of the location
 232 parameter is to shift the graph to the left or right on the horizontal axis. The scale parameter
 233 describes the stretching capacity of the probability distribution function.

234 The location parameter obtained in this study for the log-logistic distribution is
 235 approximately 7.4 for the UK's water-consumption data. The scale parameter is in between
 236 0.0107 and 0.026 (Table 2). With regard to the North American water-consumption data, the
 237 location parameter obtained for log-logistic distribution is between 3.92 and 4.562. Similarly, the
 238 scale parameter is between 0.0296 and 0.389 (Table 3). The standard deviation is in a range of
 239 1720 to 1792 and mean value is 35 to 96.51 for the UK's consumption data (Table 4).

240

241 Table 2. Location and scale parameters for log-logistic distribution for UK water demand data

Date	Location	Scale
2009 data	7.485	0.01776
2010 data	7.482	0.0256
2011 data	7.464	0.01517
2012 data	7.448	0.01068

242

243 Table 3. Location and scale parameters for log-logistic distribution for Canadian water demand
 244 data

Date	Zone 1		Zone 2		Zone 3	
	Location	Scale	Location	Scale	Location	Scale
2009 data	4.089	0.0415	4.545	0.0457	3.920	0.105
2010 data	4.089	0.0415	4.545	0.0457	3.920	0.105
2011 data	4.187	0.055	4.446	0.063	4.308	0.142
2012 data	4.098	0.389	4.361	0.041	4.152	0.092
2013 data	4.115	0.0296	4.562	0.054	3.992	0.088

245

246

247

248

249 Table 4. Standard deviation and mean values for water-consumption data for UK water demand

Data	Standard Deviation	Mean
2009 data	67.9	1792
2010 data	96.51	1787
2011 data	45.31	1746
2012 data	35	1720

250

251 CONCLUSIONS

252 It was observed that by analysing water-consumption data, 88% of the water-consumption data
253 has a positively skewed distribution. This means that data would fit better for positively skewed
254 distributions such as log-normal, log-logistic and Weibull. Following detailed analysis of data,
255 the study shows that from the four selected distribution patterns studied, the log-logistic
256 distribution provided the lowest AD values and was the most suitable water-distribution pattern
257 to standardise when modelling the water demand.

258 The findings in this study are in accordance with the literature which stated that log-
259 logistic distribution is the best fit for real water-consumption data. Although log-normal and
260 log-logistic distributions may be similar for moderate sample sizes, it is still desirable to choose a
261 more suitable model to obtain an accurate probability values at tails.

262 Moreover, the normal and log-normal distributions produced marginally acceptable AD
263 values. The AD values obtained for the Weibull distribution have higher values when compared
264 with the other three distributions (log-logistic, log-normal and normal) and were found not to be
265 suitable in simulating the water demand data.

266 To the best of the authors' knowledge, there are no prior studies which have incorporated
267 the probability of occurrence using real water-consumption data built upon a statistically
268 analysed method focused on the upper tails. Using AD test to validate the data, this study
269 focused on the data on upper tails which best represents the water-consumption data.

270 The log-logistic distribution could be used as a standard statistical distribution in
271 quantifying the probability of exceedence of the water consumption. Additionally, this work also
272 has the potential to provide, significant information to help policy makers forecast future
273 demands using a fully probabilistic method.

274

275 **ACKNOWLEDGEMENTS**

276 The authors wish to express their gratitude to the Environment Agency for supporting this
277 research initiative, and water utility companies from the UK and North America for providing
278 the data sets for this study.

279

280 **REFERENCES**

281

282 [1] Ahmad, M. I., Sinclair, C. D. & Spurr, B. D. (1988) Assessment of flood frequency
283 models using empirical distribution function statistics. *Wat. Resour. Res.* 24 (8), 1323-
284 1328

285

286 [2] Ashkar F and Mahdi S, (2006). Fitting the log-logistic distribution by generalized moments.
287 *Journal of Hydrology*, 328, 694-703

288 [3] Bao, Y. and Mays, L.W., (1990). Model for water distribution system reliability. *J. of*
289 *Hydraul. Eng.*, Vol.116(9), 1119-1137

290 [4] Bowen P T, Harp J F, Baxter W J and Shull R D, (1993). Residential water use patterns.
291 American Water Works Association - Research Foundation, USA.

292 [5] Cordeiro G M, Santana T V F, Ortega E M M and Silva G O. (2012). The
293 Kumaraswamy-LogLogistic distribution. *Journal of Statistical Theory and Applications*,
294 11, 265-291.

295 [6] De Marinis, G., Gargano, R. and Tricarico, C. (2007). Water demand models for a small
296 number of users. *ASCE Proceedings of the 8th Annual International Symposium on*
297 *Water Distribution Systems Analysis*, Cincinnati, OH, doi: 10.1061/40941(247)41.

298 [7] Dey, A. K. & Kundu, D. (2004), Discriminating between Log normal and Log logistic
299 distributions, *Journal of Statistical Computation and Simulation* vol.74, no.2, 107–121.

300 [8] El-Saidi M A, Singh K P and Bartolucci A A. (1990), A note on a characterisation of the
301 generalised log-logistic distribution. *Environmetrics*; 1 (4), 337-342.

302 [9] Gargano, R.; Tricarico, C.; Del Giudice, G.; Granata, F. (2016). A Stochastic Model for
303 Daily Residential Water Demand. *Water Sci. Technol. Water Supply* 2016, 16, 1753-
304 1767.

305 [10] Gargano, R., Tricarico, C., Granata, F., Santopietro, S., de Marinis, G. (2017).
306 Probabilistic Models for the Peak Residential Water Demand. *Water (Switzerland)*, 9,
307 417.

308 [11] Gato-Trinidad, S. and Gan, K., (2012). Characterizing maximum residential water demand.
309 *Urban Water - WIT Transactions on The Built Environment*, Vol.122, 15-24.

310

311 [12] Goulter I C and Boulchart F, (1990). Reliability constrained pipe network model, *Journal*
312 *of hydraulic engineering*, ASCE, 116, (2), 211- 227.

313 [13] Johnson R A, (2000). *Probability and statistics for Engineers*, Prentice Hall, London.

314 [14] Khomsi D, Walters G A, Thorly A R D and Ouazar D, (1996). Reliability tester for water
315 distribution networks, *Journal of Computing in Civil Engineering*, ASCE, 10, (1), 11-19.

316 [15] Kleiber C (2004). ‘Lorenz ordering of order statistics from log-logistic and related
317 distributions’, *Journal of Statistical Planning and Inference*, 120 (1-2),13-19

- 318 [16] Kwietniewski M, (2003). ‘Reliability Modelling of Water Distribution System (WDS) for
319 Operation and Maintenance Needs’, *Journal of Hydro-Engineering and Environmental*
320 *Mechanics* Vol. 51 (2004), No. 1, pp. 85–92.
- 321 [17] Mays L W, (1994). *Computer Modelling of Free Surface and Pressurised flows*,
322 Chaudray M H and Mays L W (editors), Kluwer Academic Publishers, Netherland, 485-
323 517.
- 324 [18] Montgomery D C and Runger G C, (2002). ‘Applied statistics and probability for
325 Engineers’, 3rd edition, Printed in USA.
- 326 [19] Ramos M W A, Cordeiro G, Marinho P, Dias C (2013). The Zografos-Balakrishnan Log-
327 Logistic Distribution: Properties and Applications, *Journal of Statistical Theory and*
328 *Applications*, Vol. 12, No. 3 (September 2013), 225-244
- 329 [20] Rowinski P M, Strupczewski W G and Singh V P (2001), ‘A note on the applicability of
330 log-Gumbel and log-logistic probability distributions in hydrological analyses’: *I.*
331 *Hydrological Sciences Journal*, 47 (1), 107-122.
- 332 [21] Stephens M A (1974), ‘EDF statistics for goodness of fit and some comparisons’, *J.*
333 *American Statistical Association*, Vol.69, pp. 730-737.
- 334 [22] Surendran, S., Tanyimboh, T. and Tabesh, M. (2005). Peaking demand factor-based
335 reliability analysis of water distribution systems. *Advances in Engineering Software*,
336 36(11-12), pp.789-796.96.
- 337 [23] Swamee, P.K. (2002). Near lognormal distribution. *J. Hydrol. Eng.*, 7(6), 441-444.
- 338 [24] Syntetos A. A. & Boylan, J E, (2001). On the bias of intermittent demand estimates.
339 *International Journal of Production Economics*, 71, 457– 466.
- 340 [25] Syntetos A.A, and Boylan, J E, (2005). The accuracy of intermittent demand estimates,
341 *International Journal of Forecasting* 21 (2005) 303– 314
- 342 [26] Tanyimboh T T and Surendran S, (2002). Log-logistic Distribution Models for Water
343 Demands, 4th International Conference on Engineering and Technology Civil-Comp
344 press, Sterling.
- 345 [27] Tricarico, C., de Marinis, G., Gargano, R. and Leopardi, A., (2007). Peak residential water
346 demand. *Water Management Journal*, Vol.160(WM2), pp.115-121.
- 347
- 348 [28] Xu C and Goulter I C, (1997). A New model for reliability based optimal design of water
349 distribution networks, *The 27th Congress of the International Association for Hydraulic*
350 *Research*, ASCE, 423-428.
- 351 [29] Xu C and Goulter I C, (1998). Probabilistic model for distribution reliability, *Journal of*
352 *Water Resources Planning and Management*, ASCE, 124, (4), 218-228.
- 353 [30] Xu C and Goulter I C, (1999). Reliability based optimal design of water distribution
354 networks, *Journal of Water Resources Planning and Management*, ASCE, 125, (6), 352-
355 362.
- 356