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A Weibull-Gompertz Makeham Distribution with Properties and Application to Cancer Data

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Authors' contributions

This work was carried out in collaboration between the two authors. Both authors read and approved the final manuscript.

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Abstract

The article presents an extension of the Gompertz Makeham distribution using the Weibull-G family of continuous probability distributions proposed by Tahir et al. (2016a). This new extension generates a more flexible model called Weibull-Gompertz Makeham distribution. Some statistical properties of the distribution which include the moments, survival function, hazard function and distribution of order statistics were derived and discussed. The parameters were estimated by the method of maximum likelihood and the distribution was applied to a bladder cancer data. Weibull-Gompertz Makeham distribution performed best (AIC = -6.8677, CAIC = -6.3759, BIC = 7.3924) when compared with other existing distributions of the same family to model bladder cancer data.

Keywords: Gompertz-Makeham distribution; Weibull-Gompertz Makeham distribution; hazard function; survival function; cancer.

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1 Introduction

The Gompertz-Makeham distribution (GMD) was introduced by Makeham in 1860 [1]. It is an extended model of the Gompertz probability distribution that was introduced by Gompertz in 1825 [2]. The GMD is a continuous probability distribution that has been widely used in survival analysis, modelling human mortality, constructing actuarial tables and growth models. It has been recently used in many fields of sciences including actuaries, biology, demography, gerontology, and computer science.

A comprehensive review of the history and theory of the GMD can be found in [3]. Golubev [4] emphasizes the practical importance of this probability distribution. Detailed information about the GM distribution, its mathematical and statistical properties, and its applications can be found in [5] and [6].

The cumulative distribution function (cdf) and probability density function (pdf) of the Gompertz-Makeham distribution are defined as:

$$G(x) = 1 - e^{-\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1\right)}$$
⁽¹⁾

and

$$g(x) = \left[\theta + \alpha e^{\beta x}\right] e^{-\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1\right)}$$
⁽²⁾

respectively.

For $x > 0, \alpha, \beta, \theta > 0$, where θ is the scale parameter and α and β are the shape parameters of Gompertz-Makeham distribution.

There are families of distributions proposed by different researchers that are used in extending other distributions to produce compound distributions with better performance. These families among others include the beta generalized family (Beta-G) [7], Transmuted family of distributions [8], Exponentiated T-X [9], Exponentiated-G (EG) [10], Logistic-G [11], Logistic-X [12], Weibull-X [13], Weibull-G [14], a new Weibull-G family [15], a new generalized Weibull-G family [16] and Beta Marshall-Olkin family of distributions [17] etc.

Recently, many authors have extended the Gompertz-Makeham distribution. Chukwu and Ogunde [18] introduced and studied the Kumaraswamy Gompertz Makeham distribution. El-Bar [19] used the quadratic rank transmutation map [8] to defined and study the transmuted Gompertz Makeham distribution with useful discussions as well as applications.

Hence, the aim of this article is to introduce another extension of the Gompertz Makeham model, a new continuous distribution called Weibull-Gompertz Makeham distribution (WGMD) from a proposed family [15]. The rest of this article is arranged as follows: the definition of the new distribution will be presented with its plots and some properties. These are followed by the reliability functions, the order statistics for the distribution and the maximum likelihood estimates (MLEs) of the unknown parameters. The last part involves the application of the proposed model with other models to a lifetime dataset and the conclusion.

2 Materials and Methods

2.1 Construction of Weibull-Gompertz Makeham Distribution (WGMD)

This section defines the cdf and pdf of the Weibull-Gompertz Makeham distribution (WGMD) using the family of distributions proposed [15], which has been used by other authors [20]. According to Tahir [15], the function for defining the cdf and pdf of any Weibull-based continuous distribution is given as:

$$F(x) = \int_{0}^{-\log[G(x)]} abt^{b-1} e^{-at^{b}} dt = e^{-a\left\{-\log[G(x)]\right\}^{b}}$$
(3)

and

$$f(x) = ab \frac{g(x)}{G(x)} \{ -\log[G(x)] \}^{b-1} e^{-a \{ -\log[G(x)] \}^{b}}$$
(4)

respectively, where g(x) and G(x) are the pdf and cdf of any continuous distribution to be generalized respectively. The parameters, a and b are the two additional new parameters responsible for the scale and shape of the distribution respectively.

Using equation (1) and (2) in (3) and (4) and simplifying, the cdf and pdf of the WGMD of a random variable X can be obtained as:

$$F(x) = e^{-a\left\{-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right\}^{b}}$$
(5)

and

$$f(x) = \frac{ab\left(\theta + \alpha e^{\beta x}\right)e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b-1}}{\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]e^{a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}}}$$
(6)

respectively.

For $x > 0; a, b, \theta, \alpha, \beta > 0$; where a, b, θ, α and β are the parameters of the WGMD.

The following is a graphical representation of the pdf and cdf of the WGMD using arbitrary values of the parameters a, b, θ , α and β .



Pdf of WGMD



It is observed in Fig. 1 that the WGMD is a positively skewed distribution and can take various forms. This means that distribution can be very useful for datasets that are skewed.



Cdf of WGMD

Fig. 2. A plot of CDF of the WGMD for varying parameter values

From the above cdf plot, the cdf increases when X increases, and approaches 1 when X becomes large or tends to infinity as expected.

3 Properties

In this section, we defined and discuss some properties of the WGMD distribution.

3.1 Moments

Let X denote a continuous random variable, the nth moment of X is given by;

$$\boldsymbol{\mu}_{n} = E\left[\boldsymbol{X}^{n}\right] = \int_{0}^{\infty} \boldsymbol{x}^{n} f(\boldsymbol{x}) d\boldsymbol{x}$$
⁽⁷⁾

Considering f(x) to be the pdf of the WGMD as given in equation (6)

$$\boldsymbol{\mu}_{n}^{'} = E\left[\boldsymbol{X}^{n}\right] = \int_{0}^{\infty} \boldsymbol{x}^{n} f(\boldsymbol{x}) d\boldsymbol{x}$$

Recall that from equation (6),

$$f(x) = \frac{ab\left(\theta + \alpha e^{\beta x}\right)e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b-1}}{\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]e^{a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}}}$$
(8)

To simplify the pdf in (8) above, we carryout the following operations:

Let

$$A = e^{-a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}}$$

Then, using a power series expansion for A, we can write A as:

$$A = e^{-a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}(e^{\theta x} - 1)}\right]\right)^{b}} = \sum_{i=0}^{\infty} \frac{(-1)^{i} a^{i}}{i!} \left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}(e^{\theta x} - 1)}\right]\right)^{bi}$$

Substituting for the expansion above in equation (8), we have;

$$f(x) = \frac{ab\left(\theta + \alpha e^{\beta x}\right)e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\sum_{i=0}^{\infty}\frac{\left(-1\right)^{i}a^{i}}{i!}\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{bi}}{\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{-(b-1)}}$$

$$f(x) = \frac{ab\left(\theta + \alpha e^{\beta x}\right)e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\sum_{i=0}^{\infty}\frac{\left(-1\right)^{i}a^{i}}{i!}\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{bi+(b-1)}}{\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]} \tag{9}$$

Also, let $B = \left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\theta x} - 1\right)}\right]\right)^{bi+(b-1)}$

Now, considering the following formula from [12] and [20] which holds for B for $i \ge 1$, then B can be written as follows:

$$\left(-\log\left[1-e^{-\alpha - \frac{a}{\beta}(e^{\beta k}-l)}\right]\right)^{k+(b-l)} = \sum_{k,l=0}^{\infty} \sum_{j=0}^{k} \frac{(-l)^{j+k+l}(b(i+l))}{(b(i+l)-l-j)} \binom{k-(b(i+l)-l)}{k} \binom{k}{j} \binom{b(i-l)+l}{l} + k}{l} P_{j,k} \left[1-e^{-\alpha - \frac{a}{\beta}(e^{\beta k}-l)}\right]^{j}$$
(10)

Where for (for $j \ge 0$) $P_{j,0} = 1$ and (for $k = 1, 2, \dots$)

$$P_{j,k} = k^{-1} \sum_{m=1}^{k} (-1)^{m} \frac{\left[m(j+1)-k\right]}{(m+1)} P_{j,k-m}$$
(11)

Combining equation (10) and (11) and inserting the above power series in equation (9) and simplifying, it gives:

$$f(x) = cb \sum_{i=0}^{\infty} \frac{(-1)^{i} d}{i!} \sum_{k,l=0}^{\infty} \sum_{j=0}^{k} \frac{(-1)^{j+k+l} (b(i+1))}{(b(i+1)-1-j)} \binom{k-(b(i+1)-1)}{k} \binom{k}{j} \binom{(b(i+1)-1)+k}{l} P_{j,k} \binom{\theta+\alpha e^{\beta k}}{k} e^{-\theta - \frac{\alpha}{\beta}(e^{\beta k}-1)} \left[1-e^{-\theta - \frac{\alpha}{\beta}(e^{\beta k}-1)}\right]^{-1} \frac{1}{12}$$

$$f(x) = b \sum_{i=0}^{\infty} \sum_{k,l=0}^{\infty} \frac{(-1)^{i+j+k+l} d^{i+l} (b(i+1))}{i!(b(i+1)-1-j)} \binom{k-(b(i+1)-1)}{k} \binom{k}{j} \binom{(b(i+1)-1)+k}{l} P_{j,k} \binom{\theta+\alpha e^{\beta k}}{k} e^{-\theta - \frac{\alpha}{\beta}(e^{\beta k}-1)} \left[1-e^{-\theta - \frac{\alpha}{\beta}(e^{\beta k}-1)}\right]^{-1} \frac{1}{12}$$

Now, if l is a positive non-integer, we can expand the last term in (12) as:

$$\left[1-e^{-\theta x-\frac{\alpha}{\beta}\left(e^{\beta x}-1\right)}\right]^{l-1} = \sum_{m=0}^{\infty} \left(-1\right)^m \binom{l-1}{m} \left[e^{-\theta x-\frac{\alpha}{\beta}\left(e^{\beta x}-1\right)}\right]^m$$
(13)

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Therefore, f(x) becomes:

$$f(x) = b \sum_{m=0}^{\infty} \sum_{i=0}^{\infty} \sum_{k,j=0}^{\infty} \sum_{j=0}^{k} \frac{(-1)^{i+j+k+l+m}}{i!(b(i+1)-1-j)} \binom{l-1}{m} \binom{k-(b(i+1)-1)}{k} \binom{k}{j} \binom{(b(i+1)-1)+k}{l} P_{j,k}\left(\theta + \alpha e^{\beta x}\right) e^{-(m+1)(\theta + e^{\beta x}-l)} e^{-(m+1)(\theta + e^{\beta x}-$$

Using power series expansion on the last term in equation (14), we have

$$e^{-\frac{\alpha}{\beta}(m+1)e^{\beta x}} = \sum_{r=0}^{\infty} \frac{(-1)^{r} \alpha^{r} (m+1)^{r}}{r! \beta^{r}} e^{r\beta x}$$
(15)

Now, substituting equation (15), the power series expansion in equation (14) above, one gets:

$$f(x) = b \sum_{r=0}^{\infty} \sum_{m=0}^{\infty} \sum_{i=0}^{\infty} \frac{(-1)^{i+j+k+l+mnr}}{e^{\frac{\alpha}{p}(m+l)}r!\beta i!(b(i+l)-l-j)} \binom{l-l}{m} \binom{k-(b(i+l)-l)}{k} \binom{k}{j} \binom{b(i+l)-l}{l} + k}{l} P_{jk}(\theta + \alpha e^{\beta k}) e^{-[\theta m+l-r\beta]k}$$

Now, let

$$\eta_{i,j,k,l,m,r} = b \sum_{r=0}^{\infty} \sum_{m=0}^{\infty} \sum_{i=0}^{\infty} \sum_{k,l=0}^{\infty} \sum_{j=0}^{k} \frac{(-1)^{i+j+k+l+m+r}}{e^{\frac{a(m+1)}{\beta}} r! \beta' i! (b(i+1)-1-j)} {l-1 \choose m} \binom{l-1}{m} \binom{k-(b(i+1)-1)}{k} \binom{k}{j} \binom{(b(i+1)-1)+k}{l} P_{j,k}$$

This implies that:

$$f(x) = \eta_{i,j,k,l,m,r} \left\{ \theta e^{-\left[\theta(m+1) - r\beta\right]x} + \alpha e^{-\left[\theta(m+1) - \beta(1+r)\right]x} \right\}$$
(16)

Hence,

$$\boldsymbol{\mu}_{n}^{'} = E\left(\boldsymbol{X}^{n}\right) = \int_{0}^{\infty} \boldsymbol{\chi}^{n} f(x) dx = \int_{0}^{\infty} x^{n} \left(\eta_{i,j,k,l,m,r} \left\{ \theta e^{-\left[\theta(m+1)-r\beta\right]x} + \alpha e^{-\left[\theta(m+1)-\beta(1+r)\right]x} \right\} \right) dx$$

$$\boldsymbol{\mu}_{n}^{'} = \int_{0}^{\infty} \boldsymbol{\chi}^{n} f(x) dx = \eta_{i,j,k,l,m,r} \left[\theta \int_{0}^{\infty} x^{n} e^{-\left[\theta(m+1)-r\beta\right]x} dx + \alpha \int_{0}^{\infty} x^{n} e^{-\left[\theta(m+1)-\beta(1+r)\right]x} dx \right]$$
(17)

Also, using integration by substitution method in equation (17) gives the following:

Let
$$u_1 = \left[\theta(m+1) - r\beta\right] x \Longrightarrow x = \frac{u_1}{\theta(m+1) - r\beta}$$
; $\frac{du_1}{dx} = \theta(m+1) - r\beta$ and
 $dx = \frac{du_1}{\theta(m+1) - r\beta}$

Let
$$u_2 = \left[\theta(m+1) - \beta(1+r)\right] x \Longrightarrow x = \frac{u_2}{\theta(m+1) - \beta(1+r)}$$
; $\frac{du_2}{dx} = \theta(m+1) - \beta(1+r)$ and
 $dx = \frac{du_2}{\theta(m+1) - \beta(1+r)}$

Substituting for u, x and dx in equation (17) and simplifying gives:

$$\boldsymbol{\mu}_{n}^{'} = \eta_{i,j,k,l,m,r} \left[\frac{\theta}{\left(\theta(m+1) - r\beta\right)^{n+1}} \int_{0}^{\infty} u_{1}^{n+1-1} e^{-u_{1}} du_{1} + \frac{\alpha}{\left(\theta(m+1) - \beta(1+r)\right)^{n+1}} \int_{0}^{\infty} u_{2}^{n+1-1} e^{-u_{2}} du_{2} \right]$$
(18)

Again recall that $\int_{0}^{\infty} t^{n-1}e^{-t}dt = \Gamma(n) \text{ and that } \int_{0}^{\infty} t^{n}e^{-t}dt = \int_{0}^{\infty} t^{n+1-1}e^{-t}dt = \Gamma(n+1)$

Thus, the nth ordinary moment of X for the WGMD is given as follows:

$$\boldsymbol{\mu}_{n}^{'} = \eta_{i,j,k,l,m,r} \left[\frac{\boldsymbol{\theta} \Gamma(n+1)}{\left(\boldsymbol{\theta}(m+1) - r\boldsymbol{\beta}\right)^{n+1}} + \frac{\boldsymbol{\alpha} \Gamma(n+1)}{\left(\boldsymbol{\theta}(m+1) - \boldsymbol{\beta}(1+r)\right)^{n+1}} \right]$$
(19)

3.2 The mean

The mean of the WGMD can be obtained from the n^{th} moment of the distribution when n = 1 as follows:

$$\boldsymbol{\mu}_{1} = \eta_{i,j,k,l,m,r} \left[\frac{\theta}{\left(\theta(m+1) - r\beta\right)^{2}} + \frac{\alpha}{\left(\theta(m+1) - \beta(1+r)\right)^{2}} \right]$$
(20)

3.3 The variance

The n^{th} central moment or moment about the mean of X, say μ_n , can be obtained as

$$\boldsymbol{\mu}_{n} = E \left[X - \boldsymbol{\mu}_{1}^{'} \right]^{n} = \sum_{i=0}^{n} (-1)^{i} \binom{n}{i} \boldsymbol{\mu}_{1}^{'i} \boldsymbol{\mu}_{n-i}^{'}$$
(21)

The variance of X for WGMD is obtained from the n^{th} central moment when n = 2, that is, the variance of X is the n^{th} central moment of order two (n = 2) and is given as follows:

$$Var(X) = E[X^{2}] - \{E[X]\}^{2}$$

$$Var(X) = \mu_{2} - \{\mu_{1}\}^{2}$$
(22)

$$Var(X) = \eta_{i,j,k,l,m,r} \left[\frac{2\theta}{\left(\theta(m+1) - r\beta\right)^3} + \frac{2\alpha}{\left(\theta(m+1) - \beta(1+r)\right)^3} \right] - \left\{ \eta_{i,j,k,l,m,r} \left[\frac{\theta}{\left(\theta(m+1) - r\beta\right)^2} + \frac{\alpha}{\left(\theta(m+1) - \beta(1+r)\right)^2} \right] \right\}^2 (23)$$

The coefficients variation, skewness and kurtosis measures can also be calculated from the non-central moments using some well-known relationships.

3.4 Moment generating function

The mgf of a random variable X can be obtained by

$$M_{x}(t) = E\left[e^{tx}\right] = \int_{0}^{\infty} e^{tx} f(x) dx$$
⁽²⁴⁾

Using power series expansion in equation (24) and simplifying the integral gives;

$$M_{x}(t) = \sum_{n=0}^{\infty} \frac{t^{n}}{n!} \mu_{n}^{'} = \sum_{n=0}^{\infty} \frac{t^{n}}{n!} \left\{ \eta_{i,j,k,l,m,r} \left[\frac{\theta \Gamma(n+1)}{\left(\theta(m+1) - r\beta\right)^{n+1}} + \frac{\alpha \Gamma(n+1)}{\left(\theta(m+1) - \beta(1+r)\right)^{n+1}} \right] \right\}$$
(25)

where n and t are constants, t is a real number and $\mu_{n}^{'}$ denotes the n^{th} ordinary moment of X.

3.5 Characteristic function

The characteristic function of a random variable X is given by;

$$\varphi_x(t) = E\left[e^{itx}\right] = E\left[\cos(tx) + i\sin(tx)\right] = E\left[\cos(tx)\right] + E\left[i\sin(tx)\right]$$
(26)

Simple algebra and power series expansion proves that

$$\phi_{x}(t) = \sum_{n=0}^{\infty} \frac{(-1)^{n} t^{2n}}{(2n)!} \mu_{2n}^{'} + i \sum_{n=0}^{\infty} \frac{(-1)^{n} t^{2n+1}}{(2n+1)!} \mu_{2n+1}^{'}$$
(27)

Where μ'_{2n} and μ'_{2n+1} are the moments of X for n=2n and n=2n+1 respectively and can be obtained from μ'_{n} in equation (20).

4 Some Reliability Functions

In this section, the survival and hazard functions from the WGMD are presented with adequate plots and their discussions.

4.1 The survival function

The survival function as the name implies describes the probability that a component or an individual will not fail after a given time. It is mathematically given as:

$$S(x) = 1 - F(x) \tag{28}$$

Taking F(x) to be the cdf of the WGMD, substituting and simplifying (28) above, we get the survival function for the WGMD as:

$$S(x) = 1 - e^{-a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}}$$
(29)

The following is a plot of the survival function for arbitrary parameter values.



Survival function of WGMD

Fig. 3. A plot of the survival function of WGMD

The figure above reveals that the probability of survival for any random variable following a WGMD which decreases as the time increases, that is, as time goes on, probability of life decreases as it is expected. This shows that the WGMD would be useful for modeling most real life situations.

4.2 The hazard function

Hazard function is also called failure or risk function. It describes the probability failure for a component given an interval of time. The hazard function is defined mathematically as;

$$h(x) = \frac{f(x)}{1 - F(x)} = \frac{f(x)}{S(x)}$$
(30)

Considering f(x) and F(x) to be the pdf and cdf of the proposed WGMD given previously, we obtain the hazard function as:

$$h(x) = \frac{ab\left(\theta + \alpha e^{\beta x}\right)e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b-1}e^{-a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}}}{\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\left(1 - e^{-a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}}\right)}$$
(31)

The following is a plot of the hazard function at chosen parameter values.



Hazard function of WGMD

Fig. 4. A plot of the hazard function of the WGMD

Fig. 4 above shows the behaviour of hazard function of the WGMD. It means that the probability of failure for any WGM random variable increases as the time or age of a subject increases, that is, as time goes on, the probability of failure or death increases.

5 Order Statistics

Suppose X_1, X_2, \dots, X_n is a random sample from a distribution with pdf, f(x), and $X_{1:n} < X_{2:n} < \dots < X_{i:n}$ denote the corresponding order statistic obtained from this sample. Then the pdf, $f_{i:n}(x)$ of the i^{th} order statistic can be defined as;

$$f_{i:n}(x) = \frac{n!}{(i-1)!(n-i)!} \sum_{k=0}^{n-i} (-1)^{k} {\binom{n-i}{k}} f(x) F(x)^{k+i-1}$$
(32)

where f(x) and F(x) are the pdf and cdf of the Weibull Gompertz Makeham distribution respectively.

Using (5) and (6), the pdf of the i^{th} order statistics $X_{i:n}$, can be expressed from (32) as;

$$f_{in}(x) = \frac{n!}{(i-1)!(n-i)!} \sum_{k=0}^{n-i} \left(-1\right)^{k} \binom{n-i}{k} \left[\frac{db \left(\theta + \alpha e^{\beta x}\right) \left(-\log \left[1 - e^{-\theta x - \frac{\alpha}{\beta} e^{\beta x} - 1}\right]\right)^{b-1}}{\left[1 - e^{-\theta x - \frac{\alpha}{\beta} e^{\beta x} - 1}\right]^{b} e^{\theta x - \frac{\alpha}{\beta} e^{\beta x} - 1}} \right]^{b} e^{\theta x - \frac{\alpha}{\beta} e^{\beta x} - 1} \left[e^{-\theta x - \frac{\alpha}{\beta} e^{\beta x} - 1} \right]^{b} \right]^{d+1}$$
(33)

Hence, the pdf of the minimum order statistic $X_{(1)}$ and maximum order statistic $X_{(n)}$ of the WGMD are given by;

$$f_{1n}(x) = n \sum_{k=0}^{n-1} (-1)^{k} {\binom{n-1}{k}} \left[\frac{db \left(\theta + \alpha e^{\beta x} \right) \left(-\log \left[1 - e^{-\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1 \right)} \right] \right)^{b-1}}{\left[\left[1 - e^{-\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1 \right)} \right] e^{\left(-\log \left[1 - e^{-\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1 \right)} \right] \right)^{b}} e^{\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1 \right)} \right]^{b}} \right]^{b} \left[\left[1 - e^{-\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1 \right)} \right] e^{\left(-\log \left[1 - e^{-\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1 \right)} \right] \right)^{b}} e^{\theta x - \frac{\alpha}{\beta} \left(e^{\beta x} - 1 \right)} \right]^{b}} \right]^{b} \right]^{b} \right]$$
(34)

and

$$f_{nn}(x) = n \left[\frac{ab\left(\theta + \alpha e^{\beta x}\right) \left(-\log\left[1 - e^{-\theta x - \frac{a}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b-1}}{\left[1 - e^{-\theta x - \frac{a}{\beta}\left(e^{\beta x} - 1\right)}\right]} e^{\left(-\log\left[1 - e^{-\theta x - \frac{a}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}} e^{\theta x + \frac{a}{\beta}\left(e^{\beta x} - 1\right)} \right]} \left[e^{-\left(-\log\left[1 - e^{-\theta x - \frac{a}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}} \right]^{b-1}}$$
(35)

respectively.

6 Estimation of unknown Model Parameters using Maximum Likelihood Method

Let $X_1, X_2, ..., X_n$ be a sample of size 'n' independently and identically distributed random variables from the WGMD with unknown parameters a, b, α, β and θ defined previously. The pdf of the WGMD is given from (6) as:

$$f(x) = \frac{ab\left(\theta + \alpha e^{\beta x}\right)e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b-1}e^{-a\left(-\log\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]\right)^{b}}}{\left[1 - e^{-\theta x - \frac{\alpha}{\beta}\left(e^{\beta x} - 1\right)}\right]}$$

The likelihood function is given by;

$$L(\underline{X}|a,b,\alpha,\beta,\theta) = \frac{(ab)^{n} \prod_{i=1}^{n} \left(\left(\theta + \alpha e^{\beta X_{i}} \right) e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right) \prod_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e^{-\theta x_{i} - \frac{ai}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right)^{b-1} - a \sum_{i=1}^{n} \left(-\log \left[1 - e$$

Let the log-likelihood function, $l = \log L(\underline{X} | a, b, \alpha, \beta, \theta)$, therefore

$$l = n\log a + n\log b + \sum_{i=1}^{n}\log\left(\theta + \alpha e^{\beta x_{i}}\right) - \theta \sum_{i=1}^{n} x_{i} - \frac{\alpha}{\beta} \sum_{i=1}^{n} (e^{\beta x_{i}} - 1) + (b-1) \sum_{i=1}^{n}\log\left(-\log\left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta}(e^{\beta x_{i}} - 1)}\right]\right)$$
$$-a \sum_{i=1}^{n} \left(-\log\left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta}(e^{\beta x_{i}} - 1)}\right]\right)^{b} - \sum_{i=1}^{n} \left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta}(e^{\beta x_{i}} - 1)}\right)$$
(37)

Differentiating **l** partially with respect to a, b, α, β and θ respectively gives;

$$\frac{\partial l}{\partial a} = \frac{n}{a} - \sum_{i=1}^{n} \left(-\log\left[1 - e^{-\theta x_i - \frac{\alpha}{\beta}\left(e^{\beta x_i} - 1\right)}\right] \right)^b$$
(38)

$$\frac{\partial l}{\partial b} = \frac{n}{b} + \sum_{i=1}^{n} \log\left(-\log\left[1 - e^{-\theta x_i - \frac{a}{\beta}\left(e^{\theta x_i} - 1\right)}\right]\right) - a\sum_{i=1}^{n} \left(-\log\left[1 - e^{-\theta x_i - \frac{a}{\beta}\left(e^{\theta x_i} - 1\right)}\right]\right)^b \log\left(-\log\left[1 - e^{-\theta x_i - \frac{a}{\beta}\left(e^{\theta x_i} - 1\right)}\right]\right)$$
(39)

$$\frac{\partial l}{\partial \alpha} = \sum_{i=1}^{n} \left\{ \frac{e^{\beta x_{i}}}{\theta + \alpha e^{\beta x_{i}}} \right\} - \frac{1}{\beta} \sum_{i=1}^{n} \left(e^{\beta x_{i}} - 1 \right) + \frac{(b-1)}{\beta} \sum_{i=1}^{n} \left\{ \frac{\left(e^{\beta x_{i}} - 1 \right) e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)}}{\left(-\log \left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right) \left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right) \right\}} \\ - \frac{1}{\beta} \sum_{i=1}^{n} \left\{ \frac{\left(e^{\beta x_{i}} - 1 \right) e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)}}{\left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right)} \right\} + ab \sum_{i=1}^{n} \left\{ \frac{\left(-\log \left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right] \right)^{b-1} \left(e^{\beta x_{i}} - 1 \right) e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)}}{\left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1 \right)} \right)} \right\}$$
(40)

$$\frac{\partial}{\partial\beta} = \sum_{i=1}^{n} \left\{ \frac{\alpha e^{\beta x_{i}}}{\left(\theta + \alpha e^{\beta x_{i}}\right)} \right\}^{-\frac{\alpha}{\beta}} \sum_{i=1}^{n} \left\{ x_{i} e^{\beta x_{i}} - \beta^{-1} \left(e^{\beta x_{i}} - 1\right) \right\} + \frac{\alpha \left(b-1\right)}{\beta} \sum_{i=1}^{n} \left\{ \frac{\left(x_{i} e^{\beta x_{i}} - \beta^{-1} \left(e^{\beta x_{i}} - 1\right)\right) e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}}{\left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right)} \right\}$$

$$\frac{\alpha}{\beta} \sum_{i=1}^{n} \left\{ \frac{\left(x_{i} e^{\beta x_{i}} - \beta^{-1} \left(e^{\beta x_{i}} - 1\right)\right) e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}}{\left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right)} \right\} + \frac{ab\alpha}{\beta} \sum_{i=1}^{n} \left\{ \frac{\left(-\log\left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)\right]\right)^{b-1} \left(x_{i} e^{\beta x_{i}} - \beta^{-1} \left(e^{\beta x_{i}} - 1\right)\right) e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}}{\left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right)} \right\}$$

$$(41)$$

$$\frac{\partial}{\partial \theta} = \sum_{i=1}^{n} \left\{ \frac{1}{\left(\theta + \alpha e^{\beta x_{i}}\right)} \right\} - \sum_{i=1}^{n} x_{i} - (b-1) \sum_{i=1}^{n} \left\{ \frac{x_{i} e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}}{\left(-\log\left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right]\right) \left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right)} \right\} - \sum_{i=1}^{n} \left\{ \frac{x_{i} e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}}{\left(1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right)} \right\} + ab \sum_{i=1}^{n} \left\{ \frac{\left(-\log\left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right]\right)^{b-1} x_{i} e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}{\left[1 - e^{-\theta x_{i} - \frac{\alpha}{\beta} \left(e^{\beta x_{i}} - 1\right)}\right]} \right\}$$

$$(42)$$

Equating equation (38), (39), (40), (41) and (42) to zero and solving for the solution of the non-linear system of equations gives the maximum likelihood estimates of the parameters a, b, α, β and θ respectively. However the solution cannot be obtained analytically except numerically with the aid of suitable statistical software like Python, R, SAS, etc., when data sets are given.

7 Application to a Real Life Dataset

This section presents a dataset on the remission times (in months) of a random sample of 128 bladder cancer patients with its descriptive statistics and application to some selected extensions of the Gompertz-Makeham distribution together with the classical Gompertz distribution. The performance of the Weibull Gompertz-Makeham distribution (WGMD) is compared to some families of Makeham distribution such as Kumaraswamy Gompertz Makeham distribution (KGMD), Transmuted Gompertz-Makeham distribution (TGMD), Gompertz-Makeham distribution (GMD) and the Gompertz distribution (GD).

The performance of the above listed models is ranked using some criteria such as the AIC (Akaike Information Criterion), CAIC (Consistent Akaike Information Criterion) and BIC (Bayesian Information Criterion). It is considered that the model with the smallest values of these statistics will be the best model to fit the data.

Data set: This data set represents the remission times (in months) of a random sample of 128 bladder cancer patients. It has previously been used in [21,22,23]. It is summarized as follows:

| Parameter | n | Min | Q_1 | Median | Q_3 | Mean | Max | Var | Skew | Kurt |
|-----------|-----|--------|-------|--------|--------|-------|-------|---------|--------|---------|
| Values | 128 | 0.0800 | 3.348 | 6.395 | 11.840 | 9.366 | 79.05 | 110.425 | 3.3257 | 19.1537 |
| | | | 0 | 0 | | | | | | |

| Table 1. Summary | statistics | for tl | he dataset |
|------------------|------------|--------|------------|
|------------------|------------|--------|------------|

n-sample size, Min–Minimum, Q_1 -First Quartile, Q_3 -Third Quartile, Max-Maximum, Var-Variance, Skew-Skewness, Kurt-Kurtosis

From the descriptive statistics in Table 1, it is observed that the data set is positively skewed with a very high coefficient of kurtosis and therefore suitable for flexible and skewed distributions.

From Table 2, comparing the values of the AIC, CAIC and BIC for each model, the WGMD has the best performance compared to the KGMD, TGMD GMD and GD. This is due to the decision rule which says that the distribution or model with the smallest values of the test statistics (AIC, CAIC and BIC) is taken as the most adequate or efficient model. These values also agree with the fact that generalizing any continuous distribution provides a compound distribution with a better fit than the baseline distribution [24].

| Distributions | Parameter estimates | AIC | CAIC | BIC | Ranks of models |
|---------------|--------------------------|---------|---------|---------|------------------------|
| WGMD | $\alpha = 0.006233$ | -6.8677 | -6.3759 | 7.3924 | 1 |
| | $\beta = 0.005620$ | | | | |
| | $\theta = _{0.006119}$ | | | | |
| | a = 0.006070 | | | | |
| | b = 0.004811 | | | | |
| KGMD | $\alpha = 1.4996$ | 17.3139 | 17.8057 | 31.5741 | 3 |
| | $\beta = {}_{0.0008286}$ | | | | |
| | $\theta = 3.2157$ | | | | |
| | a = 0.1934 | | | | |
| | b = 0.09415 | | | | |
| TGMD | $\alpha = _{9.7913}$ | 51.5307 | 51.8559 | 62.9388 | 5 |
| | $\beta = {}_{9.6327}$ | | | | |
| | $\theta = _{9.4246}$ | | | | |
| | $\lambda = 0.8682$ | | | | |
| GMD | $\alpha = 2.04152$ | 29.2259 | 29.4194 | 37.7820 | 4 |
| | $\beta = {}_{7.8924}$ | | | | |
| | $\theta = 7.9969$ | | | | |
| GD | $\alpha = {}_{4.5814}$ | 12.8378 | 12.9338 | 18.5418 | 2 |
| | $\beta = _{4.5809}$ | | | | |

| Table 2. The strength of the selected models using the AIC, | CAIC and BIC values of the models |
|---|-----------------------------------|
| evaluated from the maximum likelihood estimations ba | ased on the bladder cancer data |

8 Conclusion

This article proposed a new distribution called Weibull-Gompertz Makeham distribution. The statistical properties of the distribution have been derived and studied extensively. The model parameters were estimated using maximum likelihood method. The distribution (WGMD) has the best fit compared to the other four models considered in this study when applied to real life time data.

Competing Interests

Authors have declared that no competing interests exist.

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