Half normal distribution pdf

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Semi-normal distribution is a special case of folded normal and cut normal allocations. Some applications of semi-normal distribution include modeling measurement data and lifetime data. Half normal distribution uses the following parameters:ParameterDescription−∞<m<∞ Location Measurement≥0Apostolic support for semi-normal distribution is x ≥ m.Use makedist with specified parameter values to create a semi-normal HalfNormalDistribution probability distribution object. Use fitdist to customize a half-normal probability-sharing object in sample data. Use mle to calculate the semi-normal distribution parameter values from sample data without creating a probability-sharing object. For more information about working with probability distributions, see Work with probability distributions.The Statistical and Machine Learning Toolkit™ implementation of the semi-normal distribution requires a constant value for position parameter m. Therefore, neither fitdist nor mle estimate the value of parameter m when adjusting a semi-normal distribution to sample data. You can specify a value for parameter m by using the name-value pair argument 'mu'. The default value for 'mu' is 0 in both fitdist and mle. The probability density function (pdf) of the semi-normal distribution is where m is the position parameter and p is the scale parameter. If x ≤ m, then the pdf is indeterminate. To calculate the pdf of the semi-normal distribution, create a HalfNormalDistribution probability distribution object using a fitdist or makedist, and then use the pdf method to work with the object. This example shows how changing the values of mu and sigma parameters changes the shape of the pdf. Create four probability-sharing objects with different parameters.pd1 = makedist('HalfNormal'); pd2 = makedist('HalfNormal','mu','sigma',2)· pd3 = makedist('HalfNormal','mu','sigma',3)· pd4 = makedist('HalfNormal','mu','sigma',5)· Calculate the probability density functions (pdfs) of each distribution.x = 0:0.1:10; pdf1 = pdf(pd1,x)· pdf2 = pdf(pd2,x)· pdf3 = pdf(pd3,x)· pdf4 = pdf(pd4,x)· Draw the pdfs in the same shape. plot(x,pdf1,'r','LineWith',2) hold down. plot(x,pdf2,'k:','LineWith',2); plot(x,pdf3,'b-.','LineWith',2); plot(x,pdf4,'g--','LineWith',2); legend({'mu = 0, sigma = 1','mu = 0, sigma = 2',... 'mu = 0, sigma = 3','mu = 0, sigma = 5'},'Location','NE'); hold off; As the sigma increases, the curve flattens and the peak value becomes smaller. The cumulative distribution function (cdf) of the semi-normal distribution is where m is the position parameter, p is the scale parameter, erf(•) is the error function, and is the cdf of the standard normal distribution. If x ≤ m, then the cdf is not set. To calculate the cdf of the semi-normal distribution, create a halfNormalDistribution probability distribution object using a fitdist or makedist, and then use the CDF method to work with the object. This example shows how to change price values The mu and sigma parameters change the shape of the cdf. Create four probability-sharing objects with different parameters.pd1 = makedist('HalfNormal'); pd2 = makedist('HalfNormal','mu','sigma',2)· pd3 = makedist('HalfNormal','mu','sigma',3)· pd4 = makedist('HalfNormal','mu','sigma',5)· Calculate the cumulative distribution functions (cdfs) for each probability distribution.x = 0:0.1:10; cdf1 = cdf(pd1,x)· cdf2 = cdf(pd2,x)· cdf3 = cdf(pd3,x)· cdf4 = cdf(pd4,x)· Engrave all four cdfs in the same shape. plot(x,cdf1,'r','LineWith',2) hold down; plot(x,cdf2,'k:','LineWith',2); plot(x,cdf3,'b-.','LineWith',2); plot(x,cdf4,'g--','LineWith',2); legend({'mu = 0, sigma = 1','mu = 0, sigma = 2',... 'mu = 0, sigma = 3','mu = 0, sigma = 5'},'Location','SE'); hold off; As the sigma increases, the cdf curve flattens. The average of the semi-normal distribution is where m is the position parameter and p is the scale parameter. The variance of half the normal distribution is where the scale parameter is. If a random variable Z has a standard normal distribution with an average μ equal to zero and a standard deviation equal to one, then X=μ+s| Z| has a half normal distribution with parameters m and p.[1] Cooray, K. and M.M.A. Ananda. A generalization of semi-normal distribution with applications in lifetime data. Communications in Statistics - Theory and Methods. Volume 37, Number 9, 2008, p. 1323–1337. [2] Pewsey, A. Large-sample conclusion for general half normal distribution. Volume 31, Number 7, 2002, p. 1045–1054. HalfNormalDistribution Related TopicsWork with Probability DistributionSubsized distributions We study certain mathematical properties of beta generalized semi-normal distribution recently proposed by pescim et al. (2010). This model is flexible enough to analyze positive real data, since it contains as special models half-normal, exposed half-normal, and generalized semi-normal distributions. We provide a useful power range for quantile operation. Some new explicit expressions arise for mean deviations, Bonferroni and Lorenz curves, reliability and entropy. We demonstrate that the density function of the general statistics of the semi-normal beta class can be expressed as a mixture of generalized semi-normal densities. We receive two closed-ended expressions for their moments and other statistical measures. The maximum probability method is used to estimate the parameters of the model that censored data. The beta generalized semi-normal model is modified to treat long-term survivors may be present in the data. The usefulness of this distribution is reflected in the analysis of four actual datasets.1. IntroducingCooray and Ananda [1] pioneered the generalized semi-normal (GHN) with the shape parameter and scale parameter defined by the cumulative distribution function (cdf) where the standard normal CDF and the error function are given by the due to eugene et al. [2], Pescim et al. [3] proposed beta generalized semi-normal distribution (BGHN), which appears to be superior to the GHN standard for some applications. The justification for the practical application of this model is based on the development of fatigue crack under variable stress or circular load. In this paper, we study several mathematical properties of the BGHN model in the hope that it will attract broader applications in reliability, engineering and other areas of research. The four-parameter CDF BGHN is defined by (1) from (for), where the beta function is, is the incomplete beta function ratio, and is two additional schema parameters. The probability density function (pdf) and the risk rate function (hrf) corresponding to (3) are respectively. Then a random variable with pdf (4) is marked by . Pescim et al. [3] demonstrated that its cdf and pdf can be expressed as an infinite order of power of the cumulative GHN distribution. Here, all extensions in the power order are around ground zero. If it is a real noninteger, we can extend the dionymic term to (3) to get where . The pdf corresponding to (6) can be expressed as If is an integer, (7) provides the BGHN density function as an infinite power order of the cumulative GHN distribution. If it is an integer, the index of the previous total stops at . Otherwise, if it is a real noninteger, we can expand as follows: where Therefore, whose coefficients are the density function BGHN (4) allows greater flexibility of its tails and can be widely applied in many areas of engineering and biology. We study the mathematical properties of this distribution because it extends some important distributions previously examined in the literature. In fact, the GHN model, with parameters and , is clearly an important special case for , with a continuous cross-reference to models with different shapes, for example, a specific combination of unconscionability and kurtosis. The BGHN distribution also contains the exposed generalized half normal (EGHN) and semi-normal (HN) distributions as secondary models for and , respectively. Moreover, while transformation (3) is not analytically involved in the general case, the formulas associated with BGHN distribution prove manageable, and using modern computer resources with analytical and numerical capabilities, they can be converted into sufficient tools that include the arsenal of applied statisticians. The document is described as follows. We are drawing an extension for the operation of the conical in Section 2. Some statistical measures for the distribution of BGHN, such as moments, creating function, mean deviations, Rényi entropy and reliability, are studied in Section 3. Computational issues related to the infinite order for the structural properties of the BGHN are examined in Section 4. In Section 5, we draw algebraic expressions for moments, moment creation mode (mgf), average deviations, and Rényi entropy for order statistics. The assessment by the probability—including the case of censorship—is presented in Section 6. In section 7, we recommend a BGHN mix model for survival data with long-term survivors. Section 8 demonstrates the importance of the BGHN distribution applied to four actual datasets. Finally, the final comments are set out in section 9.2. The power ranges for Quantile FunctionPower series methods are at the heart of many aspects of applied mathematics and statistics. Quantile functions are widespread in probability distributions and general statistics and often find representations in terms of power series. The quantile function for a probability distribution has many uses both in theory and in the application of probability. It can be used to create values for a random variable that has as its distribution function. This serves as the basis of a method of simulating a sample from arbitrary distribution using a uniform random number generator. The quantile function of , for example , can be achieved by reversing the cumulative function (3). Now, we provide a power order extension for this may be useful to determine certain mathematical measures of BGHN distribution. First, an extension for the inverse of incomplete beta function can be found on wolfram (website as where is the beta quantile function, for and, . The s coefficients for can be obtained from a cubic flashback of the form where if and if . In the last equation, we note that the square term contributes only to . After Steinbrecher [4], the quantile function of standard normal distribution, say, can be extended as where and s can be calculated from and here, , . The function may be expressed as the order of power given by where and the quantities are determined by the coefficients in point (14) by for and for . By reversing the normal cumulative function to (3), we can express the quantile function in terms of replacement from the last equation, we will get where . Using the same steps of (8), we can write where . We use across the Gradshteyn and Ryzhik equation [5] for a power range that increases to a positive integer where the coefficients (for) are easily taken from the recurrence equation and . From (19) and (20), we have been steps for, for and . With the introduction (12) to (22), we receive from (20), following , where the quantities are determined retroactively by and (for). Finally, they will acquire where . The equation (24) gives the quantile BGHN function as a power order and represents the main result of this section.3. BGHN Properties3.1. Moments and creation FunctionHere, we provide new expressions for the moments and its mgf-based power order for operation as an alternative form effects of those obtained from Pescim et al. [3]. We can write from (24) and then using (20), we receive where the quantities (for) are easily determined by the recurrence equation with . We are now providing a new alternative representation for mgf mgf , say , based on the quantile power order (24). We can write Expand the exponential function and use the same algebra that leads to (26) and then Equations (26) and (30) are the main results of this section.3.2. Average and Median Deviations The amount of dispersion in a population is obviously measured to some extent by the mean deviations from the mean and median values defined by respectively, where it indicates the median value. Here, it is calculated as the solution of the nonlinear equation. We define, which is specified below. The measures can also be written in terms and as for more details, see Paranaíba et al. [6]. Clearly, and determined by (3). From (10), we set in the last equation gives Using the power order for error mode (see, e.g., [7]), we receive after some algebra where it indicates the complementary incomplete gamma function for . The measures and shall be calculated immediately from (35). Bonferroni and Lorenz curves have applications not only in economics for the study of income and poverty, but also in other areas such as reliability, demography, insurance and medicine. They are defined respectively, where and (section 2) for a given probability . Since , we have received and .3.3. Rényi EntropyRényi information of the class for a continuous random variable with density function is defined as where , and . Applications of Rényi entropy can be found in various fields such as physics, information theory and engineering to describe many nonlinear dynamic or chaotic systems [8], and in statistics as certain appropriately scaled test statistics (relevant Rényi information) for test hypotheses in parametric models [9]. Rényi [10] generalizes the concept of information theory that allows the different average of probabilities through . For the distribution of BGHN (4), Rényi entropy is defined by where , and . Since (4), we have for we are a real noninteger, the power range holds where the (for) are defined by (10). Using (40) in (39) twice, can be expressed as Substitution by error function and setting, reduces to After similar algebra leading to (35), we finally receive Rényi entropy reduced to 3.4. Reliability In the context of reliability, the stress resistance model describes the life of an element that has a random force subjected to random stress. The component fails once the pressure applied to it exceeds the strength, and the component will function satisfactorily whenever. Therefore, it is a measure of the reliability of the components. Here, we draw when and have independent and distributions with the same shape parameters and . Reliability becomes where cdf and density are obtained from (6) and (10) as respectively, where indicated and , respectively. Therefore, Setup in the last its reliability is reduced to 4. Computational TopicsHere, we show the practical use of (24), (26), (30), (35) and (49). If we cut these infinite ranges of power, power, have a simple way to calculate the quantile function, moments, mgf, mean deviations and reliability of the BGHN distribution. The question is how big should the cut limit be? We are now providing evidence that any infinite sum can be cut to twenty to yield sufficient accuracy. Let's indicate the absolute difference between the built-in version, where there is a uniform variable in the unit interval, and the cut-off version of the (24) average (all step), and . Let's indicate the absolute difference between the built-in version and the cut version (26) that has an average relative to , , and . Let's indicate the absolute difference between the cut version of (35) and the built-in version, which has an average relative to , , and . Let's indicate the absolute difference between the cut version of (30) and the built-in version, which has an average relative to , , and . Let's indicate the absolute difference between the cut version (49) and the built-in version (45), on average over , , and . We receive the following estimates after extensive calculations: , , and . These estimates are small enough to suggest that the cut-off versions of (24), (26), (30), (35) and (49) are reasonable practical use. It would be important to verify that each (untrue) infinite order (such as (24), (26), (30), (35) and (49)) is convergent and provides valid values for its definitions. However, this will be a difficult mathematical problem that could be explored in future work.5. The properties of BGHN Order StatisticsOrder statistics have been used in a wide range of problems, including strong statistical assessment and detection of extreme values, probability allocations and good fit tests, entropy assessment, analysis of sample censorship, reliability analysis, quality control and material strength.5.1. The FormSuppose Mix is a random sample from a continuous distribution and let's indicate the corresponding order statistics. A lot of work has been done on order statistics moments. See Arnold et al. [11], David and Nagaraja [12], and Ahsanullah and Nevzorov [13] for excellent accounts. It is known that its density function is given by for the distribution BGHN, Pescim et al. [3] obtained where it indicates a sequence of non-pure integers, indicates the density function defined below and the constants given by Quantities are easily taken for granted and a sequence of indicators . The amounts in (55) span all tuples () and can be applied to a computer. If it is an integer(55), but the indicators vary from zero to . The equation (55) reveals that the density function of BGHN statistical orders can be expressed as infinite BGHN.5.2 densities. Order Statistics MomentsBGHN order statistics can be written directly for BGHN distribution moments from the mix format (55). We have where and we can identify by (26). Insert (26) in (57) and change change we can write where Moments can be determined based on the explicit amount (58) using the Mathematica software. They are also calculated from (55) with numerical integration using the statistical software R [14]. The values of both techniques are usually close when replaced by a moderate number, as in (58). For some values, and , table 1 lists the numeric values for points , (;) and variance, gradient, and kurtosis. Order statistics 2.67942 5.81946 4.73975 1.71571 0.23289 18.10007 39.31172 32.01807 11.59006 11.59006 1.57328 127.8683 277.7184 226.1923 81.87821 11.11451 938.314 2037.933 1659.1828 600.8327 81.55966Variance10.92078 5.44561 9.55281 8.64636 1.51904Skysysyness0.57767 −1.1.1 13596 −0.54601 1.27135 5.36291Kurtosis1.61751 4.06406 1.89737 2.91095 31.076425.3. Production functionGgf of BGHN statistical orders can be written directly in terms of mgf BGHN in the form of a mixture (55) and (30). We receive where is the mgf of the BGHN distribution obtained from (30).5.4. Average deviations The average deviations of statistical orders in relation to the average and median are determined respectively, indicating the median value. Here, it is taken as a solution of the non-linear equation The measures follow from where . Using (55), we have where taken from (35) using given by (59) and where Bonferroni and Lorenz curves of statistical orders are given by respectively, where and are given by , indicating the median value. From , we get 5.5. Rényi EntropyRényi entropy of statistical orders is determined by where , and . From (54), it appears that using (40) in (70) will gain for and , we can expand as well as then Therefore, from (70), we can write By replacing both (10) and (16) given by Pescim et al. [3], we have Using the ID (for positive integer) in (4), we have where Using the power order (40) in (76) twice and replacing by the error function (defined in section 3.2) we receive after some algebra where the quantity is well defined by pescim et al. [3]. (More details, see equation in [3]). Finally, the entropy of statistical orders can be expressed as Equation (79) is the main result of this section. Pescim et al. [3] proposed an alternative extension for the density function of identity-derived order statistics. Appendix A.6 lists a representation of the second density function and alternative expressions for certain measures of statistical orders. Lifetime AnalysisLet is a random variable with density mode (4), where it is the vector of parameters. The data found in survival analysis and reliability studies are often censored. A very simple random censorship mechanism that is often realistic is one in the each person is considered to have a life and a year of censorship, where they are independent random variables. Assume that the data consists of independent observations about . Its distribution does not depend on any of the unknown parameters of its distribution. Parametric conclusion for these are usually based on probability methods and their asymptotic theory. The censored probability of recording for the model parameters is where the number of failures is located and indicates the uns censored and censored sets of observations, respectively. The score functions for the parameters , , and are given from where and is the icamma function. Its maximum probability estimate (MLE) is achieved by numerical resolution of nonlinear equations , and . We can use repetitive techniques such as the Newton-Raphson-type algorithm to obtain the estimate. We use the NLMoxed subroutine in SAS [15]. To estimate the interval and test assumptions about these parameters we receive the observed information matrix, since the expected information matrix is very complex and will require numerical integration. The table of information observed is whose elements are listed in Appendix B. The normal approach applies if it is replaced by , i.e. by the table of information observed in the address . The normal multi-variable distribution can be used to construct approximate confidence intervals for model parameters. The statistical relationship to the probability ratio (LR) can be used to test the suitability of the BGHN distribution and to compare this distribution with some of its specific submodels. We can calculate the maximum values of unlimited and limited recording probabilities for constructing LR statistics to test certain submodel of the BGHN distribution. For example, we can use the LR statistic to check whether the customization using the BGHN distribution is statistically superior to an adjustment using the modified Weibull distribution or weibull superscript for a given data set. In any case, the case check of the formula against can be performed using LR statistics. For example, the versus test is equivalent to comparing the EGHN and BGHN distributions. In this case, the LR statistic becomes where , , and the MLEs are down and , and are the estimates in the section . We stress that first-rate asymptotic results for LR statistics can be misleading for small sample sizes. Future research may be conducted to draw detailed or bootstrap Bartlett corrections.7. A BGHN model for survival data with long-term cancer studies based on population SurvivorsIn, treatment is said to occur when mortality in the group of cancer patients returns to the same level as expected general population. The treatment fraction is of interest to patients and also a useful measure when analyzing trends in the survival of cancer patients. Models for survival analysis usually assume that each subject in the study population is sensitive to the event under study and will eventually experience such an event if the monitoring is large enough. However, there are cases where a fraction of people are not expected to of interest, i.e. these individuals are cured or are not sensitive. For example, researchers may be interested in analyzing the recurrence of a disease. Many people may never experience a repeat? Therefore, there is a therapeutic fraction of the population. Treatment rate models have been used to estimate the cured fraction. These models are survival models that allow a therapeutic fraction of individuals. These models broaden the understanding of time-event data, allowing for more accurate and informative conclusions. These conclusions are otherwise inaccessible from an analysis that does not take into account a cured or unacceptable fraction of the population. If a cured ingredient is not present, the analysis reduces to standard approaches of survival analysis. Treatment rate models have been used to model time-to-event data for various types of cancers, including breast cancer, non-Hodgkins lymphoma, leukemia, prostate cancer, and melanoma. Perhaps the most popular type of treatment rate models is the mixture model introduced by Berkson and Gage [16] and Maller and Zhou [17]. In this model, the population is divided into two subpopulations, so that a person is either cured with probability, or has a proper survival function with probability. This gives an inappropriate function of surviving populations in the form of the mixture, that is, The common options for means (84) are the exponential and Distributions of Weibull. Here, we adopt BGHN distribution. The mix models for these distributions have been studied by several authors, including Farewell [18], Sy and Taylor [19] and Ortega et al. [20]. The book by Maller and Zhou [17] provides a wide range of applications of the long-term survivor mix model. The use of survival models with fraction therapy has become increasingly common because traditional survival analysis does not allow the modelling of data in which non-homogeneous parts of the population do not represent the fact of interest even after long monitoring. Now, we recommend an application of BGHN distribution to compose a mix model to estimate the treatment rate. Consider a sample, where it is either the observed lifetime or censorship time for the person. Leave a binary random variable for , indicating that the person in a population is at risk or not in relation to a particular type of failure, that is, indicates that the person will eventually experience a failure event (without validation) and indicates that the person will never experience such an event (cured). For an individual, the percentage of the non-timed can be determined so that the conditional distribution of it is given by . Assume that 's are independent and identical distributed random variables the BGHN distribution with density mode (4). The maximum probability method is used to estimate parameters. Thus, the contribution of a person who has not been able to function in the probability is provided by is at risk from time to time is the new model defined by (85) and (86) called the BGHN mix model with long-term survivors. For, we take the GHN mix model (a new model) with long-term survivors. Thus, the log-probability function for the parameter vector results from (85) and (86) as to where and indicate the totals of individuals corresponding to lifetime observations and censorship times, respectively, and is the number of uncensored observations (failures).8. ApplicationsIn this section, we give four applications using known datasets (three censored and one uncensored dataset) to demonstrate the flexibility and applicability of the proposed model. The reason for selecting this data is that they allow us to show how in different areas it is necessary to have positive asymmetric distributions with non-acant support. These datasets show different degrees of gradient and kurtosis.8.1. Censored data: TransistorThe first dataset consists of the lifetime of transistors in an accelerated life test. Three of the lives are censored, so the censorship fraction is 3/34 (or 8.8%). Wilk et al. [21] stated that there is a reason, from previous experience, to expect that gamma distribution could reasonably approach the distribution of failure time. Wilk et al. [21] and also Lawless [22] installed a gamma distribution. Alternatively, we include the BGHN model in this data. We estimate the parameters, and by maximum probability. The MLES of the allocation and for the allocation of GHN are taken as starting values for the iterative process. The calculations were carried out in accordance with the NLMixed procedure in SAS [15]. Table 2 lists the SMEs (and corresponding standard errors in parentheses) of the model parameters and the values of the following statistics for some models: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Consec Consistent Akaike Information Criterion (CAIC). The results show that the BGHN model has the lowest AIC, BIC and CAIC values and could therefore be chosen as the best model. In addition, we calculate the maximum unlimited and limited recording probabilities and LR statistics for testing certain submodels. For example, the LR statistic for testing cases : versus : not true, that is, to compare the BGHN and GHN models, is (value =0.0027), which gives a favorable indication to the BGHN model. In a specific one, the Weibull density function given by Figure 1(a) shows the plots of empirical survival function and the estimated survival functions of the BGHN, GHN and Weibull distributions. We achieve a good adaptation of the BGHN model to this data. Model AIC CAIC BGHN 0.0479 (0.0062) (2.8892) 400.87 (0.4000) 1 92.13 (0.2480) 248.2 2 49.6 254.3 GHN 0.9223 (0.1361) 25.7408 (3.8627) 1 (—) 1 (—) 256.0 256.4 259.1 Weibull 20.7819 (2.8215) 1.3 414 (0,1721) 263,4 267,8 270,4 (a) (b) point (c) (b) (c)8.2. Censored data: RadiotherapyThe data refer to survival time (days) for cancer patients () undergoing [23]. The percentage of censored comments was. By placing the BGHN distribution on this data, we receive the SMEs of the model parameters listed in Table 3. The values of the AIC, CAIC and BIC statistics are lower for the BGHN distribution compared to the GHN and Weibull distribution values. The LR statistic for the test of cases : against : it is not true, that is, to compare the BGHN and GHN models, is (value = 0.0022), which produces a favourable indication to the BGHN distribution. Thus, this distribution seems to be a very competitive model for analyzing lifetime data. Figure 1(b) shows the observatories of empirical survival mode and estimated survival functions for the BGHN, GHN and Weibull distributions. We note a good application of BGHN distribution. Model AIC CAIC BGHN 0.0456 (0.0051) 540.40 (108.19) 223.66 (0.4313) 112.38 (0.1560) 594.6 595 ,5 602.3 GHN 0.7074 (0.0879) 533.45 (88.6917) 1 (—) 1 (—) 602.8 603.1 606.7 Weibull 361.. 76 (52.4678) 1.0239 (0.1062) 705.7 706.0 709.6 8.3. Uncensored Data: USS Halfbeak Diesel EngineHere, we compare the crises of BGHN, GHN, and Weibull distributions with the dataset presented by Ascher and Feingold [24] from a USS Halfbeak (submarine) diesel engine. The data indicate 73 failure times (in hours) of unplanned maintenance operations for the main propulsion diesel engine USS Halfbeak over 25,518 hours of operation. Table 4 provides the MLEs of the model parameters. The values of the AIC, CAIC and BIC statistics are lower for the BGHN distribution compared to the GHN and Weibull distribution values. The LR statistic for testing cases : against : it is not true, that is, to compare the BGHN and GHN models, is (value 0.0001), which indicates that the first distribution is superior to the second in terms of model adjustment. Figure 1(c) shows the observatories of the empirical survival function and the estimated survival function of the BGHN, GHN and Weibull distributions. In fact, BGHN distribution provides a better adaptation to this data. Model AIC CAIC BGHN 7.0649 (0.0027) 18.9581 (0.0027) 0.2368 (0.04 1 6) 0.1015 (0.0134) 400.2 401.6 409.3 GHN 3.8208 (0.4150 21.8838 (0.4969) 1 (—) 1 (—) 438.4 439.0 442.9 Weibull 21.1 1 1972 (0.6034) 4.2716 (0.4627) 455.5 456.1 460.1 8.4. Melanoma data with long-term survivorsWe provide an application of the BGHN model to cancer recurrence. The data are part of a study on skin melanoma (a type of malignant cancer) to assess the postoperative performance of treatment with a high dose of a particular drug (interferon alfa-2b) in order to avoid recurrence. Patients were included in the study from 1991 to 1995 and follow-up until 1998. The data were collected by Ibrahim et al. [25]. Survival time is defined as the time until the patient's death. The original sample size was weak, 10 of which did not show a value for explanatory variable volume thickness. When these cases were abolished, they were abolished, size of patients. The percentage of censored comments was. Table 5 lists the MNs of the model parameters. The values of the AIC, CAIC and BIC statistics are lower for the BGHN mixture model compared to the values of the GHN mixture model. The LR statistic for testing assumptions : versus : not true, that is, to compare the models bghn and ghn mixture, is done (value 0.0001), which indicates that the BGHN mixture model is superior to the GHN mix model in terms of model adjustment. Figure 2 provides observatories of the empirical survival function and estimated survival functions of the bghn and GHN mixture models. Please note that the ratio calculated by the BGHN mixture model is more appropriate than that estimated by the GHN mixture model. In addition, the BGHN blend model provides a better adaptation to this data. Model AIC CAIC BGHN Mix 0.4871 (0.0349) 0.2579 (0.0197)54.8258 (17.2126)19.4970 (1.0753)40.9300 (2.2931)1059.5 1059.6 1079 .6 Mixture GHN 0.5150 (0.0279) 1.2553 (0.0799) 2.5090 (0.1475) 1 (—) 1 (—) 1074.1 1074.2 1086.2 In this paper, we discuss some mathematical properties of the beta generalized half normal distribution (BGHN) recently introduced by pescim et al. [3]. Integrating additional parameters provides a very flexible model. We draw a power range extension for the quantile BGHN function. We provide some new structural properties such as moments, producing function, mean deviations, Rényi entropy, and reliability. We investigate the properties of order statistics. The maximum probability method is used to estimate model parameters for uncensored and censored data. We also propose a BGHN model for survival data with long-term survivors. Applications in four actual datasets show that the BGHN model provides a flexible alternative to (and a better application than) some classic lifetime models. AppendicesA. Appendix A Here, we draw some properties of BGHN order statistics. Using the ID in Gradshteyn and Ryzhik [5] and after some algebraic manipulations, we receive an alternative form for the density function of the statistical order th, that is, where it indicates the density of the BGHN distribution and the quantity is defined by Pescim et al. [3]. From (A.1), we receive alternative expressions for the moments and mgf of the BGHN statistical orders given by the average deviations of statistical orders relative to the average and median value can be expressed respectively, where , and defined in section 5.4. We use (A.1) to get where it comes from (35). The Bonferroni and Lorenz curves of the statistical series are defined, in section 5.4, from respectively, where . From, these can also be expressed as Use (A.4), we receive bonferroni and Lorenz curves for BGHN.B. Order Statistics Annex B Here, we give the necessary formulas to obtain the few second-class derivatives of the recording probability function. After some algebraic manipulations, we get where where the authors would like to thank the author, the deputy editor and the arbitrators for their careful reading of the newspaper and for their comments, which significantly improved the paper. Refers.