International Journal of Scientific Advances
ISSN: 2708-7972
Volume: 4 | Issue: 3 | May – Jun 2023 Available Online: www.ijscia.com
DOI: 10.51542/ijscia.v4i3.9

# Comparing the Performance of a Survival Models In a Computerized Dataset

**Farouq Ndamadu Musa[1], Bilkisu Muhammad Bello[2], and Ibrahim Aliyu Hassan[3*]**

[1]Department of Maths and Statistics, Kaduna Polytechnic, Kaduna
[2]Department of Computer Science, Kaduna Polytechnic, Kaduna
[3]Department of Environmental Science, Kaduna Polytechnic, Kaduna

*Corresponding author details: Ibrahim Aliyu Hassan;
aliyuibrahim@kadunapolytechnic.edu.ng

## ABSTRACT

Every patient demonstrates the loss of one year of healthy life. In addition, 7.6% of global DALYs are assigned to the neoplasms. The three leading cancers in both sexes worldwide were lung cancer (13% of the total), breast cancer (11.9%), and colorectal cancer (9.7%); the most common types of cancer in men, respectively, are lung cancer (16.8%), prostate cancer (14.8%) and colorectal cancer (10.1%) while in women they are ordered as breast cancer (25.1%), colorectal cancer (9.2%) and lung cancer (8.8%). The research aimed to compare the performance of Weibull, Log-logistics, and Gompertz survival models on oncological data. The research methodology involved the collection of data cases on oncological study analyzed using descriptive statistics, parametric survival models were also used in the analysis. The result shows the maximum likelihood estimates of dataset 1 with 3 with a different model fit, all the information criteria and log-likelihood of the models indicate that Gompertz model has the smallest value in all the information criteria, indicating that Gompertz model is the best-fitted model to Remission Times of Bladder Cancer patient's data. The research concludes that a parametric that can best be used to model cancer data known as Gompertz model is the best-used model in the research. The research will enable other researchers such as medical personnel to model or know the best model for cancer-related cases.

***Keywords:*** cancer; dataset; Gompertz; compare; performance

## INTRODUCTION

Previous literature has shown that most researchers employed the used of parametric survival model without putting into cognizance the most effective model to be used on oncological data in the survey. Researchers used a different approach to solve this problem by trying to identify the factors that cause cancer and also worked on the best model to be employed to control the effect of the disease, however, most of them used logistic regression for this purpose which may not be the accurate model to detect the factors since it deals mostly with probability rather than survival time and gives its outcome in terms of odd ratio. Other researchers used Cox-regression, Chi-square, and other descriptive statistics such as frequency and percentage to identify the factors without checking to see if other models will perform better in identifying this problem. Given the limitation of the existing research, it will be difficult to generalize the identified factors as the prognostic factors associated with the timings and hence, the need to compare models to get the best model that will give accurate data on risk factors associated with the timing of the years of infection of the disease (cancer) where this research will cover.

The lack of detailed and analytic studies on the risk factors of Breast cancer in Nigerian presents us with the challenge of not knowing the risk factors distinct to the Nigerian settings. Effectively handling breast cancer treatment in co-infected patients is delicate.

## LITERATURE REVIEW

The review provides conceptual sources and empirical studies to Comparative Study on The Performance of Weibull, Log-Logistic, and Gompertz Survival Models on Oncological Data.

### Conceptual Framework

The occurrence of survival (or time-to-event) data is commonplace in medical research, where interest lies in the time it takes from a given baseline, for an event of interest to occur, and the factors that are associated with it. For example, this could be the effect of a treatment on the time to death since diagnosis of cardiovascular disease. The two main approaches to survival analysis, are the semi-parametric approach of Cox (1972), and fully parametric approaches, assuming such distributions as the exponential or Weibull, for example (Collett, 2003). The Cox model does not assume any functional form for the baseline hazard function, whereas a parametric approach assumes a specific shape, estimated as part of the model. Both allow us to investigate the influence that risk factors have on the rate of disease or mortality, for example. In this research we would want to concentrate on the parametric approach to survival analysis, in particular, deriving a general algorithm to simulate survival data under more biologically plausible scenarios to better assess both methods used in practice, and novel models.

**Types of Approaches in Survival Analysis**

Depending on the objective of the time-to-event analysis, different modeling approaches can be used.

**1). Non-parametric models:** These models do not require assumptions on the shape of the hazard or survival function. These tests can check if the survival differs between sub-populations and the main limitations of this approach are that only categorical covariates can be tested and the way the survival is affected by the covariate cannot be assessed. Examples of these types of models are Kaplan-mier and log-rank tests.

**2). Semi-parametric models:** These are models that have a finite-dimensional parameter of interest (parametric component) and an infinite dimensional nuisance parameter (non-parametric component) as given by Begun *et al.* (1983). They assume that the hazard can be written as a baseline hazard (that depends only on time), multiplied by a term that depends only on the covariates (and not time). Under this hypothesis of proportional covariate effect, one can analyze the effect of covariates which can either be categorical or continuous in a parametric way, leaving the baseline hazard undefined. An example of this model is the Cox proportional hazard model.

**3). Parametric models:** these models require a fully specified the hazard function and their statistical test are more powerful than semi-parametric or non-parametric model if a good model can be found and the assumption of parametric is fulfilled. In this type of model, there are no restrictions on how the covariates affect the hazard and they can easily be used for predictions. Examples of these models are Gompertz, Weibull, exponential, generalized gamma, gamma, lognormal and log logistic.

However, this study will make use of parametric approaches only for the purpose of comparison.

**Empirical review**

Cancer is the name given to a collection of related diseases. Cancer can start almost anywhere in the human body, which is made up of trillions of cells. It is one of the leading causes of death in the world and represents a tremendous burden on patients, families and societies. There were 12.7 million new cancer cases in worldwide, of which 5.6 million occurred in developed countries and 7.1 million in developing countries. The corresponding estimates for total cancer deaths were 7.6 million 2.8 million in developed countries and 4.8 million in developing countries. There were an estimated 4.9 million new cases and 0.266 million global deaths from cervical cancer accounting for 7.5% of all female cancer deaths. Cervical cancer is one of the leading causes of death in the world and represents a tremendous burden on patients, families and societies. It is estimated that over one million women worldwide currently have cervical cancer; most of them have not been diagnosed or have no access to treatment that could cure them or prolong their lives Survival data is a term used for describing data that measure a time to the occurrence of a given event of interest. In this study the event of interest is survival time of cervical cancer patients from the day of diagnosis. One of the major aims of this analysis was to assess the survival of women with cervical cancer using various parametric frailty models. Kaplan and Meier obtained one important development in non-parametric methods. The non-parametric methods work well for homogeneous samples; they do not determine whether certain variables are related to the survival times. The Cox PH model has the restriction that proportional hazards assumption holds with time-fixed covariates; and it may not be appropriate in many situations and other modifications such as stratified Cox model or Cox model with time-dependent variables are required. Times. Although the Cox regression model is the most favorable employed technique in survival analysis, parametric models do have a number of benefits.

**Theoretical Review**

Survival analysis is one of the primary statistical methods for analyzing data on time to an event which is a data that has an end point. That is the time when an event occurs such as death but may include other kinds of events which can either be positive or negative such as time to discharge or time to recovering, heart attack, device failure, etc. These data analysis is important for different legal proceedings which include estimating cost of future medical care, years of life lost, evaluating product reliability, and assessing drug safety and so on. This branch of empirical science entails gathering and analyzing data on time until failure or death. Survival analysis includes different types of data analysis including life table analysis, time to failure methods, and time to death analysis.

**RESEARCH METHODOLOGY**

**Research Design**

Data cases on oncological study is used in this study, obtained from internet sources and publications. Descriptive Statistics of dataset is performed using mean, median, mode, variance, skewness, and kurtosis. Parametric survival models are used in the analysis. The models are Weibull, Log-logistics and Gompertz models, the models are chosen because of their similarities in order to have better basis for comparison and also have differences that will cater to the situation where the other one fails. The models are fitted to the data with the view to find the best fit. R statistical package was used for analyzing the data.

**Survival analysis**

A survival model is used to analyze time-to-event data and to generate estimates, referred to as *survival curves*, that show how the probability of the event occurring changes over time. In many life situations, as time progresses, certain events are more likely to occur. The survival models help decision-makers to form better estimates than guessing about the expected timing of certain events. There are three types of survival model: parametric model, semi-parametric model, and non-parametric model, parametric model is the model selected for this design.

**Time to Event Data**

Time-to-event (TTE) data is unique because the outcome of interest is not only whether or not an event occurred, but also when that event occurred. Traditional methods of logistic and linear regression are not suited to be able to include both the event and time aspects as the outcome in the model. Traditional regression methods also are not equipped to handle censoring, a special type of missing data that occurs in time-to-event analyses when subjects do not experience the event of interest during the follow-up time. In the presence of censoring, the true time to event is underestimated. Special techniques for TTE data, as will be discussed below, have been developed to utilize the partial information on each subject with censored data and provide unbiased survival estimates.

**DATA ANALYSIS AND PRESENTATION**

**1. Descriptive Statistics**

The table presents measures of location using the mean, median mode and measures of dispersion using variance, skewness, and kurtosis, the minimum, maximum and the sample sizes are also presented.

**TABLE 1:** Descriptive Statistics of the Variables.

| Data | Mean | Median | Mode | Variance | Skewness | Kurtosis | Minimum | Maximum | n |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 9.36562 | 6.395 | 5 | 110.425 | 3.28657 | 15.4831 | 0.08 | 79.05 | 128 |
| 2 | 17.6325 | 12.401 | 5 | 252.572 | 1.06609 | 0.10351 | 0.03 | 60.625 | 101 |
| 3 | 1.34144 | 0.841 | 0.25 | 1.55401 | 0.97215 | -0.3362 | 0.047 | 4.033 | 45 |
| 4 | 1.95924 | 1.7362 | 1.5 | 2.47741 | 1.97956 | 5.16079 | 0.0251 | 9.096 | 76 |
| 5 | 0.8526 | 0.9 | 0.7,0.9 | 0.11201 | 0.17219 | 0.31555 | 0.1 | 2 | 346 |

***Source:*** Field Survey, 2022.

Table 1 shows the description of data used in the analysis, dataset 1 through 5 are Remission Times of Bladder Cancer Patients, Myelogenous leukemia data, Survival times of a group of patients given chemotherapy, Fatigue Fracture data, and Nicotine measurements respectively.

## 2. Survival Analysis on Remission Times of Bladder Cancer Patients

**TABLE 2:** MLE's and Information Criteria of models for Remission Times of Bladder Cancer Patients.

| Model | $\hat{\alpha}$ | $\hat{\beta}$ | AIC | CAIC | BIC | HQIC | LL |
|---|---|---|---|---|---|---|---|
| **Weibull** | 1.96431 | 1.12646 | 932.452 | 932.548 | 938.156 | 934.769 | 464.226 |
| **Log-logistic** | 1.964312 | 1.126458 | 932.4515 | 932.5475 | 938.1556 | 934.7691 | 464.2258 |
| **Gompertz** | 0.024758 | 1.5861422 | 903.9576 | 904.0536 | 909.6616 | 906.2752 | 449.9788 |

***Source:*** Field Survey, 2022.

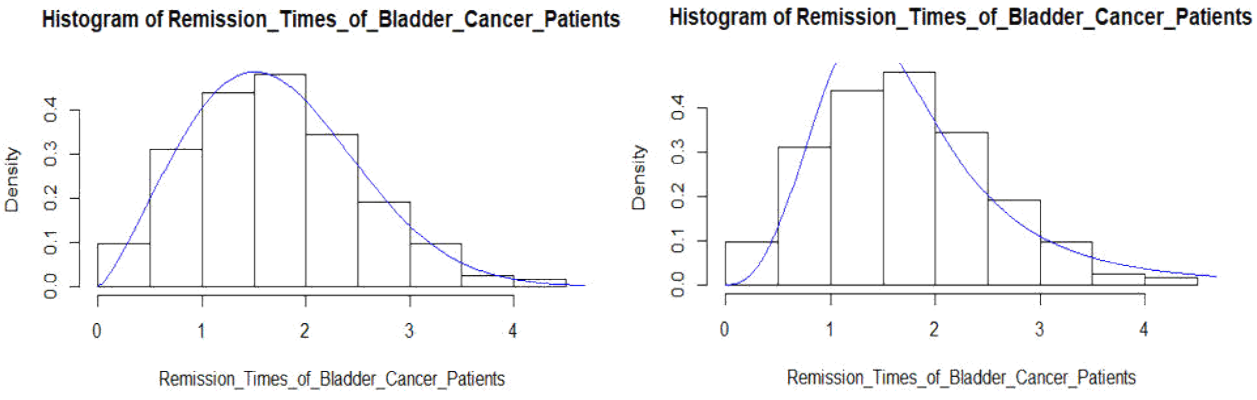
Table 2 shows the maximum likelihood estimates of dataset 1 with 3 with different model fit, all the information criteria and log-likelihood of the models indicate that, Gompertz model has smallest value in all the information criteria, indicating that Gompertz model is the best fitted model to Remission Times of Bladder Cancer patient's data.

**TABLE 3:** One Sample test about the distribution of dataset for Remission Times of Bladder Cancer Patients (Dataset1).

| Distribution | W | A | Kolmogorov-Smirnov test | |
|---|---|---|---|---|
| | | | D | p-value |
| **Weibull** | 0.2664455 | 1.593023 | 0.59415 | < 2.2e-16 |
| **Log-logistics** | 0.1770686 | 1.174072 | 0.40853 | < 2.2e-16 |
| **Gompertz** | 0.3032234 | 1.804689 | 0.3568 | 1.399e-14 |

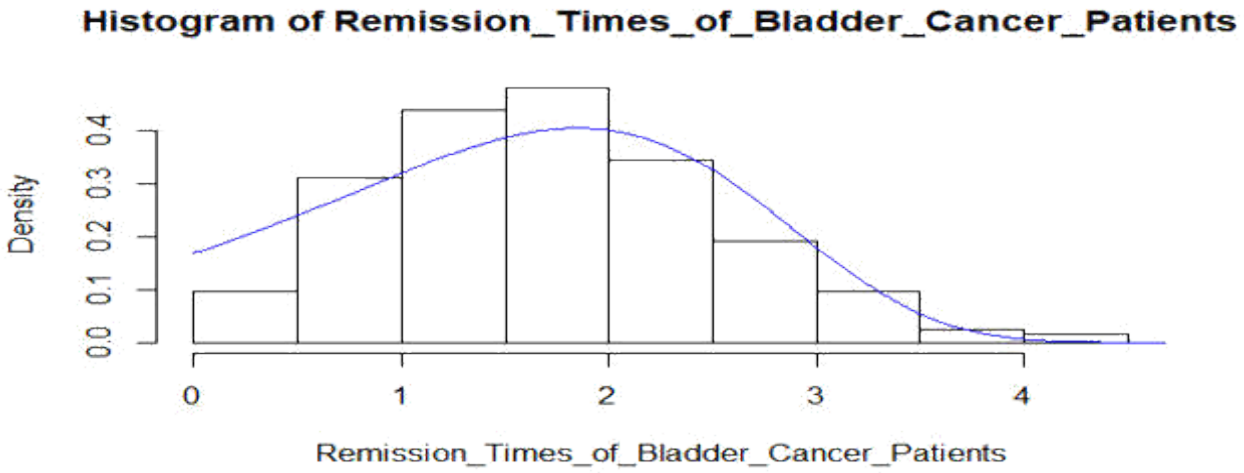
***Source:*** Field Survey, 2022

Table 3 presents the Cramer-von Misses (W), the Anderson Darling (A) and the Kolmogorov Smirnov (D) statistics, it is observed that the Gompertz distribution has greater p-value than other distributions, indicating that Gompertz distribution is the best fit for Remission Times of Bladder Cancer Patients.




(A) (B)

(A) Weibull and (B) Log-logistic.
***Source:*** Field Survey, 2022.




(C) Gompertz.
***Source:*** Field Survey, 2022.

**FIGURE 1:** Fitted curve of the three distributions for Remission Times of Bladder Cancer Patients.

### 3. Survival Analysis of Myelogenous Leukemia Data

**TABLE 4:** MLE's and Information Criteria of models for Myelogenous leukemia.

| Model | $\hat{\alpha}$ | $\hat{\beta}$ | AIC | CAIC | BIC | HQIC | LL |
|---|---|---|---|---|---|---|---|
| **Weibull** | 1.98536 | 0.83554 | 918.609 | 918.732 | 923.840 | 920.727 | 457.304 |
| **Log-logistic** | 1.9853681 | 0.836643 | 918.6094 | 918.7319 | 923.8397 | 920.7268 | 457.3047 |
| **Gompertz** | 0.0261552 | 1.673465 | 795.9594 | 796.0818 | 801.1896 | 798.0767 | 395.9797 |

***Source:*** Field Survey, 2022.

Table 4 shows the maximum likelihood estimates of dataset2 with 3 with different model fit, all the information criteria and log-likelihood of the models, Gompertz model has smallest value in all the information criteria, which indicates that Gompertz model is the best fitted model to Myelogenous leukemia data.

**SUMMARY OF FINDINGS**

Based on the analysis carried out, the following findings were made;

- Gompertz model was the best fitted model to Remission Times of Bladder Cancer patients' data, and Gompertz distribution is the best fit distribution for the data
- Gompertz model and Gompertz distribution was also the best fit to Myelogenous leukemia data
- Gompertz model was the best fitted model to survival times of a group of patients given chemotherapy treatment data, while log-logistic distribution is the best fit distribution for the data
- Weibull and log-logistic models perform better than Gompertz model in fatigue fracture data, while log-logistic distribution is the best fit for the data
- Gompertz model and the distribution was the best fit to nicotine measurements.

**CONCLUSION**

Based on the analysis carried out, it was concluded that Gompertz model was the best fit in the oncological data, followed by the Log-logistic model, Weibull and Log-logistic model behave similarly on the dataset.

**CONTRIBUTION**

The research has shown that most of the research conducted on oncological data (cancer related cases) has shown that there is scarcity of research on related cases on survival model that can best be used to model cancer related data. Therefore, the research was able to identify a parametric that can best be used to model cancer data known as Gompertz model was the best used model on the research. The research will enable other researcher such as medical personnel to model or know the best model on cancer related cases.

**REFERENCES**

[1] Abouammoh, A. M., Abdulghani, S. A., and Qamber, I. S. (1994). On partial orderings and testing of new better than renewal used classed. Reliable eng. Syst. Saftey, 43, 37-41.

[2] Andrews, D. F., Herzberg, A. M. (2012). Data: a collection of problems from many fields for the student and research worker. Springer Science Business Media.

[3] Feigl and Zelen (1965): Survival times (in months) of sample of 101 patients with Advanced Acute Myelogenous leukemia CBN.*Journal of Applied Statistics* Vol. 8 No. 2 (December, 2017)

[4] Gieser P.W., Chang M.N., Rao P.V., Shuster J.J. and Pullen J. (1998). Modelling cure rates using the Gompertz model with covariate information. Stat Med 17(8):831–839. http://www.ftc.gov/reports/tobacco or http://pw1.netcom.com/rdavis2/smoke.html

[5] P. E. Oguntunde, A. O. Adejumo& K. A. Adepoju (2016). Assessing the Flexibility of the Exponentiated Generalized Exponential Distribution, *Pacific Journal of Science and Technology*, 17(1), 49-57

[6] ferlay *et. al.* (2014). Cancer Epidemiol Biomarkers prev2014; 23:963-966 published online.

[7] Gould, C., Froese, T., Barrett, A. B., Ward, J., and Seth, A. K. (2014). An extended case study on the phenomenology of spatial form synaesthesia. *Front. Hum. Neurosci.* 8:433. doi:10.3389/fnhum.2014.00433

**APPENDICES**

**APPENDIX I: DATASETS**

**Dataset 1**

Remission_Times_of_Bladder_Cancer_Patients (source)
(0.08,2.09,3.48,4.87,6.94,8.66,13.11,23.63,0.20,2.23,3.52, 4.98,6.97,9.02,13.29,0.40,2.26,3.57,5.06,7.09,9.22,13.80,2 5.74,0.50,2.46,3.64,5.09,7.26,9.47,14.24,25.82,0.51,2.54,3. 70,5.17,7.28,9.74,14.76,26.31,0.81,2.62,3.82,5.32,7.32,10. 06,14.77,32.15,2.64,3.88,5.32,7.39,10.34,14.83,34.26,0.90 ,2.69,4.18,5.34,7.59,10.66,15.96,36.66,1.05,2.69,4.23,5.41, 7.62,10.75,16.62,43.01,1.19,2.75,4.26,5.41,7.63,17.12,46. 12,1.26,2.83,4.33,5.49,7.66,11.25,17.14,79.05,1.35,2.87,5. 62,7.87,11.64,17.36,1.40,3.02,4.34,5.71,7.93,11.79,18.10, 1.46,4.40,5.85,8.26,11.98,19.13,1.76,3.25,4.50,6.25,8.37,1 2.02,2.02,3.31,4.51,6.54,8.53,12.03,20.28,2.02,3.36,6.76,1 2.07,21.73,2.07,3.36,6.93,8.65,12.63,22.69)

**Dataset2**

Myelogenous leukemia
(0.03, 8.882, 41.118, 6.151, 17.303, 0.493, 9.145, 45.033, 6.217, 17.664, 0.855, 11.48, 46.053, 6.447, 18.092, 1.184, 11.513, 46.941, 8.651, 18.092, 1.283, 12.105, 48.289, 8.717, 18.750, 1.48, 12.796 ,57.401, 9.441, 20.625, 1.776, 12.993, 58.322, 10.329, 23.158, 2.138, 13.849, 60.625, 11.48, 27.73, 2.5, 16.612, 0.658, 12.007, 31.184, 2.763, 17.138, 0.822, 12.007, 32.434, 2.993, 20.066, 1.414, 12.237, 35.921, 3.224, 20.329, 2.5, 12.401, 42.237, 3.421, 22.368, 3.322, 13.059, 44.638, 4.178, 26.776, 3.816, 14.474, 46.48, 4.441, 28.717, 4.737, 15, 47.467, 5.691, 28.717, 4.836, 15.461, 48.322, 5.855, 32.928, 4.934, 15.757, 56.086, 6.941, 33.783, 5.033, 16.48, 6.941, 34.211, 5.757, 16.711, 7.993, 34.77, 5.855, 17.204, 8.882, 39.539, 5.987, 17.237)

**Dataset3**

survival_times_of_a_group_of_patients_given_chemotherapy_treatment
(0.047, 0.115, 0.121, 0.132, 0.164, 0.197, 0.203, 0.260, 0.282, 0.296, 0.334, 0.395, 0.458, 0.466, 0.501, 0.507, 0.529, 0.534, 0.540, 0.641, 0.644, 0.696, 0.841, 0.863, 1.099, 1.219, 1.271, 1.326, 1.447, 1.485, 1.553, 1.581, 1.589, 2.178, 2.343, 2.416, 2.444, 2.825, 2.830, 3.578, 3.658, 3.743, 3.978, 4.003, 4.033)

**Dataset4**

Fatigue_Fracture
(0.0251, 0.0886, 0.0891, 0.2501, 0.3113, 0.3451, 0.4763, 0.5650, 0.5671, 0.6566, 0.6748, 0.6751, 0.6753, 0.7696, 0.8375, 0.8391, 0.8425, 0.8645, 0.8851, 0.9113, 0.9120, 0.9836, 1.0483, 1.0596, 1.0773, 1.1733, 1.2570, 1.2766, 1.2985, 1.3211, 1.3503, 1.3551, 1.4595, 1.4880, 1.5728, 1.5733, 1.7083, 1.7263, 1.7460, 1.7630, 1.7746 , 1.8275, 1.8375, 1.8503, 1.8808, 1.8878, 1.8881, 1.9316, 1.9558, 2.0048, 2.0408, 2.03.903, 2.1093, 2.1330, 2.2100, 2.2460, 2.2878, 2.3203, 2.3470, 2.3513, 2.4951, 2.5260, 2.9911, 3.0256, 3.2678, 3.4045, 3.4846, 3.7433, 3.7455, 3.9143, 4.8073, 5.4005, 5.4435, 5.5295, 6.5541, 9.0960)

**Dataset5**

Nicotine_Measurements
(1.3, 1.0, 1.2, 0.9, 1.1, 0.8, 0.5, 1.0, 0.7, 0.5, 1.7, 1.1, 0.8, 0.5, 1.2, 0.8, 1.1, 0.9, 1.2, 0.9, 0.8, 0.6, 0.3, 0.8, 0.6, 0.4, 1.1, 1.1, 0.2, 0.8, 0.5, 1.1, 0.1, 0.8, 1.7, 1.0, 0.8, 1.0, 0.8, 1.0, 0.2, 0.8, 0.4, 1.0, 0.2, 0.8, 1.4, 0.8, 0.5, 1.1, 0.9, 1.3, 0.9, 0.4, 1.4, 0.9, 0.5, 1.7, 0.9, 0.8, 0.8, 1.2, 0.9, 0.8, 0.5, 1.0, 0.6, 0.1, 0.2, 0.5, 0.1, 0.1, 0.9, 0.6, 0.9, 0.6, 1.2, 1.5, 1.1, 1.4, 1.2, 1.7, 1.4, 1.0, 0.7, 0.4,0.9, 0.7, 0.8, 0.7, 0.4, 0.9, 0.6, 0.4, 1.2, 2.0, 0.7, 0.5, 0.9, 0.5, 0.9, 0.7, 0.9, 0.7, 0.4, 1.0, 0.7, 0.9, 0.7, 0.5, 1.3, 0.9, 0.8, 1.0, 0.7, 0.7, 0.6, 0.8, 1.1, 0.9, 0.9, 0.8, 0.8, 0.7, 0.7, 0.4, 0.5, 0.4, 0.9, 0.9 , 0.7, 1.0, 1.0, 0.7, 1.3, 1.0, 1.1, 1.1, 0.9, 1.1, 0.8, 1.0, 0.7, 1.6, 0.8, 0.6, 0.8, 0.6, 1.2,0.9, 0.6, 0.8, 1.0, 0.5, 0.8, 1.0, 1.1, 0.8, 0.8, 0.5, 1.1, 0.8, 0.9, 1.1, 0.8, 1.2, 1.1, 1.2, 1.1, 1.2, 0.2, 0.5, 0.7, 0.2,0.5, 0.6, 0.1, 0.4, 0.6, 0.2, 0.5, 1.1, 0.8, 0.6, 1.1, 0.9, 0.6, 0.3, 0.9, 0.8, 0.8, 0.6, 0.4, 1.2, 1.3, 1.0,0.6, 1.2, 0.9, 1.2, 0.9, 0.5, 0.8, 1.0, 0.7, 0.9, 1.0, 0.1, 0.2, 0.1, 0.1, 1.1, 1.0, 1.1, 0.7, 1.1, 0.7, 1.8, 1.2, 0.9, 1.7, 1.2, 1.3, 1.2, 0.9, 0.7, 0.7, 1.2, 1.0, 0.9, 1.6, 0.8, 0.8, 1.1, 1.1, 0.8, 0.6, 1.0, 0.8, 1.1,0.8, 0.5, 1.5, 1.1, 0.8, 0.6, 1.1, 0.8, 1.1, 0.8, 1.5, 1.1, 0.8, 0.4, 1.0, 0.8, 1.4, 0.9, 0.9, 1.0, 0.9, 1.3, 0.8, 1.0, 0.5, 1.0, 0.7, 0.5, 1.4, 1.2, 0.9, 1.1, 0.9, 1.1, 1.0, 0.9, 1.2, 0.9, 1.2, 0.9, 0.5, 0.9, 0.7, 0.3,1.0, 0.6, 1.0, 0.9, 1.0, 1.1, 0.8, 0.5, 1.1, 0.8, 1.2, 0.8, 0.5, 1.5, 1.5, 1.0, 0.8,1.0, 0.5, 1.7, 0.3, 0.6, 0.6, 0.4, 0.5, 0.5, 0.7, 0.4, 0.5, 0.8, 0.5, 1.3, 0.9, 1.3, 0.9, 0.5, 1.2, 0.9, 1.1, 0.9, 0.5, 0.7, 0.5, 1.1 , 1.1, 0.5, 0.8, 0.6, 1.2, 0.8, 0.4, 1.3, 0.8, 0.5, 1.2, 0.7, 0.5, 0.9, 1.3, 0.8, 1.2, 0.9).