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A Robust Approach for Best Probability Distribution Model Selection for Optimal Analysis of Radio Signals

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Abstract: Probabilistic parametric functions such as density and distribution functions modeled to depict certain stochastic behaviour are used to express the fundamental theories of reliability engineering. In the existing works of literature, a few probability distribution functions have been well reported. However, selecting and identifying the most suitable distribution functions to reliably model and fit datasets remain. This work examines the application of three different methods for selecting the best function to model and fit measured data. The methods comprise the parametric maximum likelihood estimation, Akaike Information Criteria and the Bayesian Information Criteria. In particular, these methods are implemented on Signal Interference to Noise Ratio (SINR) data acquired over an operational Long Term Evolution (LTE) mobile broadband networks in a typical built-up indoor and outdoor campus environment for three months. Generally, results showed a high level of consistency with the Kolmogorov-Semirnov Criteria. Specifically, the Weibull distribution function showed the most credible performance for radio signal analysis in the three study locations. The explored approach in this paper would find useful applications in modeling, design and management of cellular network resources.

Index Terms: Stochastic radio signals, Parametric models, Density functions, Distribution functions, Reliability, Probabilistic modeling.

1. Introduction

In-depth prognostic processing and analysis of stochastic signal data is a special signal processing practice in Spatio-temporal domains and has been an active research area for researchers in science, engineering and related fields. This is because of such practice usefulness in designing, planning, and managing cellular mobile broadband telecom system networks and resources [1–3].

Generally, propagated signals over a real multipath fading environment usually display complex and multifarious characteristics such as nonlinear properties and non-Gaussian distribution relating diverse to manmade, natural, and social factors [1, 4]. Moreover, the observation signal data are usually infected by all forms of external noise coupled with other unknown statistical, structural or physical properties [5]. In this kind of condition, in order to appraise the impact of the multipath complex environment, a precise estimation of the characteristic parameters is required.

The probability density functions and their cumulative distribution models are usually applied in stochastic signal prognostic analysis, realistic time-series modelling, and detection of the inherent radio signal characteristics over multipath terrains. However, determining the most suitable probability density and the governing parametric estimation parameters remains an important issue that needs to be investigated.

In the existing literature, several studies have projected different statistical probability distribution functions and their associated parametric estimations [6–15]. In particular, the work in [6] presented an analytical algorithm that has a three-parameter Weibull distribution function. The function was employed to estimate the reliability of a raw data sample. In [7], point estimators utilizing a three-parameters for exponential Weibull distribution with complete data and type II censored data are presented. The work in [8] presents a comparative analysis of the Weibull distribution for the errors-in-variables, combined with maximum likelihood estimates (MLE) and least square estimation (LSE) techniques. The results reported by the authors show that the MLE produced the most consistent parameter estimates in comparison with the results achieved using the errors-in-variables approach. The authors of the work in [9] studied different types of least-squares estimators compared with a three-parameter Weibull distribution for a complete sample. Additionally, the work in [10] examined the LSE method based on double Type-II censored samples. The weighted MLEs with unbiased estimators are investigated in [11]. Additionally, an innovative reliability estimation framework that employs the physics of the failure based approach is reported by [12]. The results of their study revealed that there is a relationship between physics performance and its failure mechanisms. The authors of the work in [13] reported a life prediction method suitable for a momentum wheel in a dynamic covariate environment. In [14], the concept of product reliability analysis using the Alsalam cement factory was elaborated, employing the Weibull distribution function [14]. In a related study, a reliability estimation of towed grader attachment employing the Weibull distribution, point estimation, finite element analysis and others was presented [15].

Though a number of the probability distribution functions are available, there is a dearth of research studies on how to effectively select and/or identify the most suitable one among them for reliably modelling and fitting a specific dataset.

In order to address this problem, this paper proposes and applies three different methods for the effective selection of the best function to model and fit real-time signal datasets. The methods employed are the parametric maximum likelihood estimation, Akaike Information Criteria and the Bayesian Information Criteria. The main contributions are highlighted as follows. Presented and explored contemporary methods of identifying and selecting the best probability distribution functions for analysing a stochastic signal dataset. The methods are parametric maximum likelihood estimation, Akaike Information Criteria and Bayesian Information Criteria. These methods are implemented on Signal Interference to Noise Ratio (SINR) data acquired over an operational Long Term Evolution (LTE) mobile broadband networks, in a typical built-up indoor and outdoor campus environment for three months.

The remaining part of this paper is organized as follows. Section 2 captures the theoretical framework. Section 3 projects the methods and measurements campaign. Section 4 presents the results and offers useful discussions. Finally, Section gives the concluding remarks.

2. Theoretical Framework

Specifically, this work examines the application of three different methods for selecting the best function to model and fit data. The methods are parametric maximum likelihood estimation, Akaike Information Criteria and Bayesian Information Criteria. Employing SatAssist 5.6 and MATLAB 2018a software, these methods were implemented on SINR data acquired over an operational LTE mobile broadband networks, in a typical built-up indoor and outdoor campus environment for three months. The results obtained using the different methods showed a high level of consistency with the results obtained using the commonly applied Kolmogorov-Semirnov criteria.

A. Maximum Likelihood Estimator

There are a number of techniques used for estimating unknown parameters from a given data. The key ones among them are LSE techniques and MLE techniques. The LSE method can be deployed to find the connection between a dependent variable and an independent variable. The LSE gives the best result with smaller and complete data sample sizes. The MLE involves the use of a likelihood function to look out for the values of the parameter estimates that maximize the likelihood function based on the given data. In particular, the MLE is used for parameter estimation due to its simplicity and desirable features [16]. For instance, let $x_1, x_2, x_3, \ldots\ldots x_n$ be a set of statistically measurable random variables or number trials for *n* observations" connected to a probability distribution function, $f(x,q,r)$, where q and r are the unknown location and scale parameters. The corresponding likelihood function, LF and Log-likelihood function, LLF of the independent random sample number, can be defined as:

$$LF = \prod_{i=1}^{n} f_{xi}(x_i, q, r) \tag{1}$$

$$LFF = \sum_{i=1}^{n} f_{xi}(x_i, q, r) \tag{2}$$

There exist a number of LLF probability distribution models whose parameters can be determined using the MLE approach [16, 17]. The key probability distribution functions engaged in this research paper are Generalized extreme value (Gev), Weibull, Gamma, Lognormal and Rayleigh are presented in Table 1.

Table 1. Description of the key probability functions applied in this work

Distribution model	Probability distribution function (PDF)
Lognormal	$f(x,q,r) = \frac{1}{xr\sqrt{2\pi}} \exp\left[\frac{-(\ln x - q)^2}{2r^2}\right]$
Gamma	$f(x,q,r) = \frac{1}{r^q \Gamma(q)} (x)^{q-1} \exp\left[-\left(\frac{x}{r}\right)\right]$
GEV	$f(x/0,q,r) = \frac{1}{r} \exp\left[-\exp\left(-\frac{(x-q)}{r}\right) - -\frac{(x-q)}{r}\right]$
Rayleigh	$f(x,r) = \frac{x}{r^2} \exp\left[-\left(\frac{-x^2}{2r^2}\right)\right]$
Weibull	$f(x,\lambda,c) = \frac{r}{q}\left(\frac{x}{q}\right)^{q-1} \exp\left[-\left(\frac{x}{q}\right)^r\right]$

B. Akaike information criterion (AIC) Estimator

In statistics, AIC is an estimator that provides a means of selecting the most credible model fit for a given set of data. That is, given a number of statistical models to be fitted to data, AIC provides means to accurately determine the quality of each model best fit, in correspondence to the data. The most credible model is the one with the minimum AIC value. AIC is defined as [17, 19, 21]:

$$AIC = -2LogLikelihood + 2k \tag{3}$$

where k and n indicate the estimated parameters number and number of observations in the model.

C. Bayesian information criterion (BIC) Estimator

The BIC, also known as SIC (Schwarz information criterion) for selecting the most credible model fit for a given dataset. BIC has a close connection with both MLE and AIC. Given a number of statistical models to be fitted to data, the most credible or preferred model is the one with the lowest BIC value. BIC is defined in [17, 19, 22, 23]:

$$BIC = -2LogLikelihood + k(\ln n) \tag{4}$$

where k and n indicates the estimated parameters number and number of observations in the model.

D. Goodness of Fit (GoF) Test: Kolmogorov–Smirnov Test

The goodness of fit (GoF) test is a type of test used for testing if a given sample of data fits a distribution from a certain population. There exist a number of GoF tests in the literature, but the selected one for this work is the Kolmogorov–Smirnov (K-S) test due to its flexibility and simplicity:

For a two-tailed test, The K-S statistic is given by [18]:

$$D = \sup_x |F_0(x)| - F_{data}(x) \tag{5}$$

where $F_{data}(x)$ and $F_0(x)$ indicate the corresponding empirical distribution function of the measured data and the cumulative distribution function of the posited distribution.

3. Methodology

This paper explores the exploratory data analysis (EDA) method [24] to identify and select best the probability distribution functions for the analysis of the stochastic signal dataset. As illustrated in Fig. 1, EDA is a distinctive method of exploring relevant models and systematic data analytics procedures to conduct satisfactory research. Such EDA method was also engaged in our previous works in [25, 26, 27] for field strength and COVID- data analysis.

In this paper, we combined the parametric maximum likelihood estimation model, Akaike Information Criteria and Bayesian Information criteria to identify and select best the probability distribution functions for analysis of the stochastic signal dataset. A description of the study location is provided in detail in this section. The computer script coding, graphics visualization, computations and data analysis, were implemented 2018a version of MATLAB software.

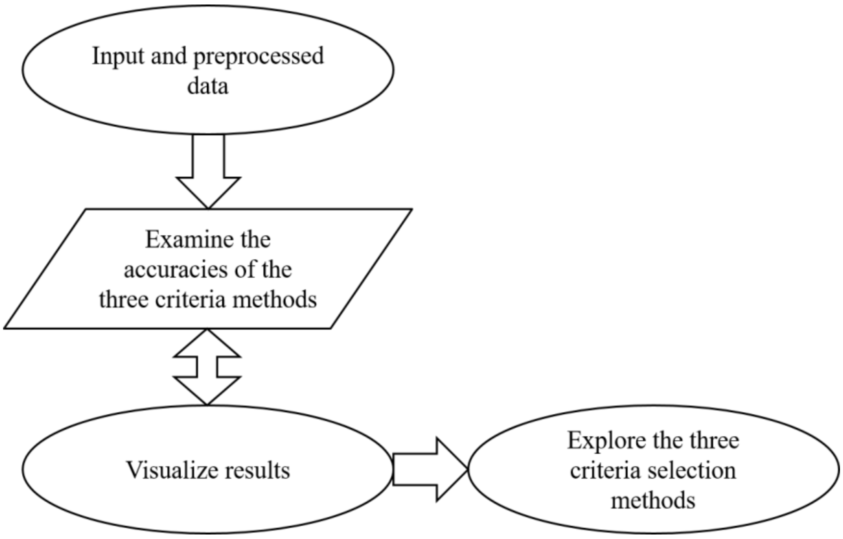

Fig. 1. Employed Exploratory Data analysis (EDA) method

A. Location of Study

A measurement campaign was conducted at the Federal University of Lokoja, Nigeria. Lokoja is a confluence town at the intersection of rivers Niger and Benue in Nigeria. The first set of measurements was taken inside and outside the Physics laboratory of the University. The second two measurement locations are inside and outside the University auditorium. Last, the third two locations are inside and outside the ASUU building at the Federal University Lokoja, Nigeria.

B. Experimental Work: Method of Data Collection

The Samsung Galaxy S4 GT-I9505 phone-based walk testing system was used in the measurement campaign. Basically, it is a TEMS pocket phone for testing and measuring various network parameters [27-30]. Initially, the network signal info and cellular Z were installed on the Samsung Galaxy S4 GT-I9505 to measure and obtain Key Performance Indicators (KPIs) information from an operational LTE cellular network located in the vicinity of the measurement location. Employing the Cellular Z, the measured signal coverage and quality of service parameters were obtained from each measurement location and sent to a dedicated email address for storage, and extracted to MATLAB for further processing. The walk tests were conducted in Lokoja in May and June of 2019. Specifically, the measurements were taken in three locations at the Federal University Lokoja. The steps employed for the Phone-based walk testing are given as follows in subsection C.

C. Walk Test Procedure

a) Determine the test location and the measurement routes
b) Obtain the coordinates of the measurement location.
c) Determine the distance of the serving eNodeB from the position of the mobile station
d) Deploy the setup and establish the LTE network connection to start a measurement campaign.
e) Send the measured data to the dedicated email server.
f) Verify successful transfer of measured data to the email server.
g) Complete the testing procedure
h) Finalize data extraction

4. Results and Discussion

The software and hardware tools employed in this study include the relevant coding, graphics and data analysis. Particularly, by means of the Cellular Z software installed in a field test phone, measured data was saved in a dedicated email server for storage and extracted to MATLAB for processing.

The results attained from the stochastic SINR data fitting analysis based on the functions of five different probability distribution models are presented in Figs. 2 to 7. The results are summarized in Tables 1 to 3 and Figs. 8 to

10 display the most fitted functions to the tested data using the MLE, AIC and BIC selection criteria. The model with the minimum AIC and BIC values is selected as the most credible model. It can be observed from Tables 1 to 3 that the GEV and Weibull are the most credible distributions in the three study locations.

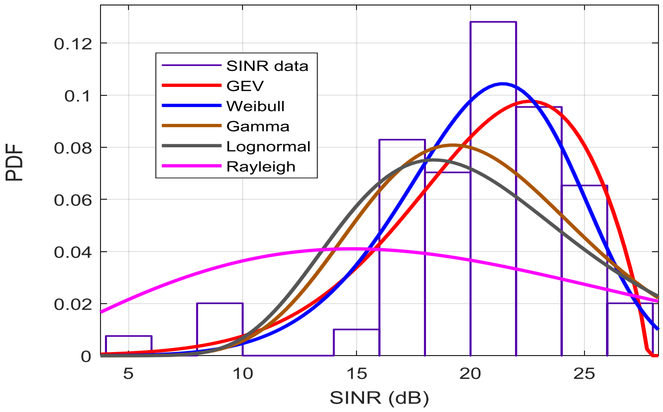

Fig. 2. Fitted PDF of tested five distribution models in L1 (outdoor)

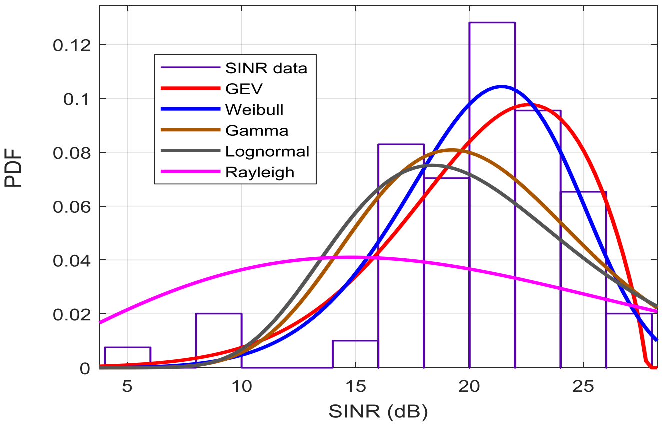

Fig. 3. Fitted PDF of tested five distribution models in L2 (outdoor)

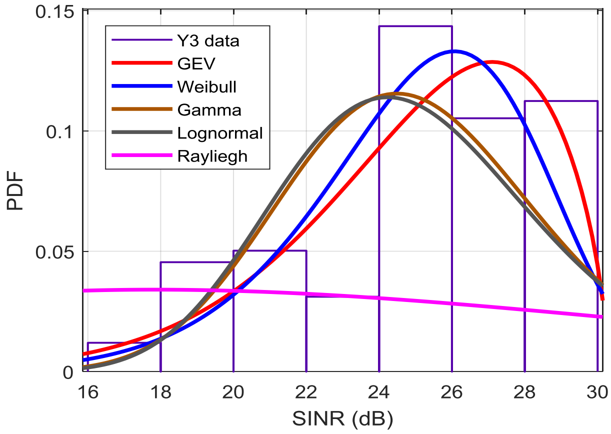

Fig. 4. Fitted PDF of tested five distribution models in L3 (outdoor).

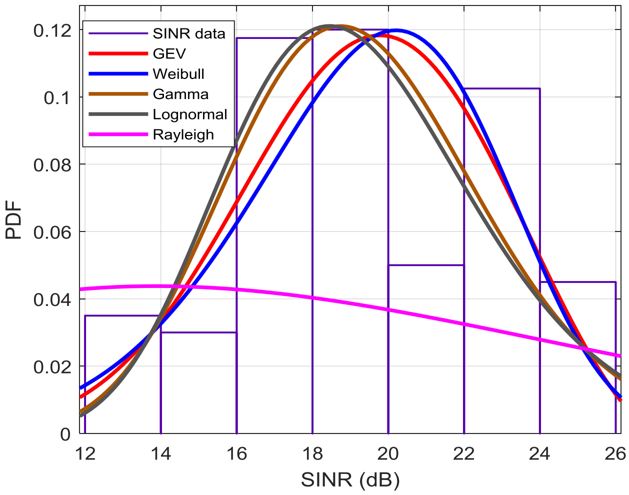

Fig. 5. Fitted PDF of tested five distribution models in L1 (indoor).

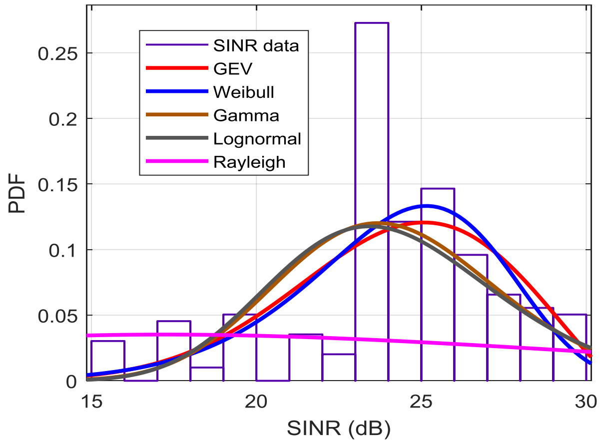

Fig. 6. Fitted PDF of studied five distribution models in L2 (indoor).

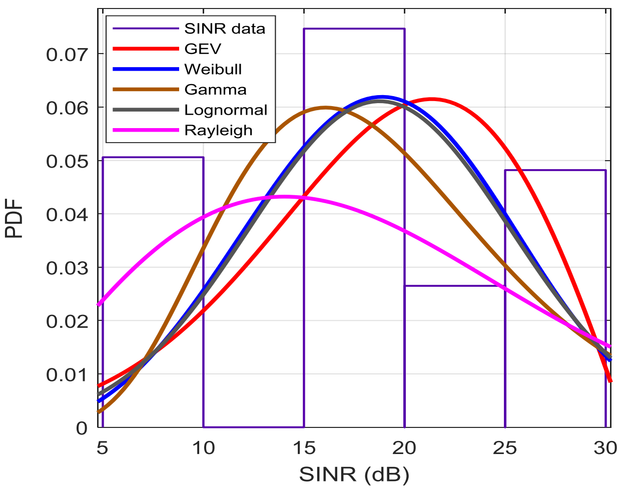

Fig. 7. Fitted PDF of studied five distribution models in L3 (indoor).

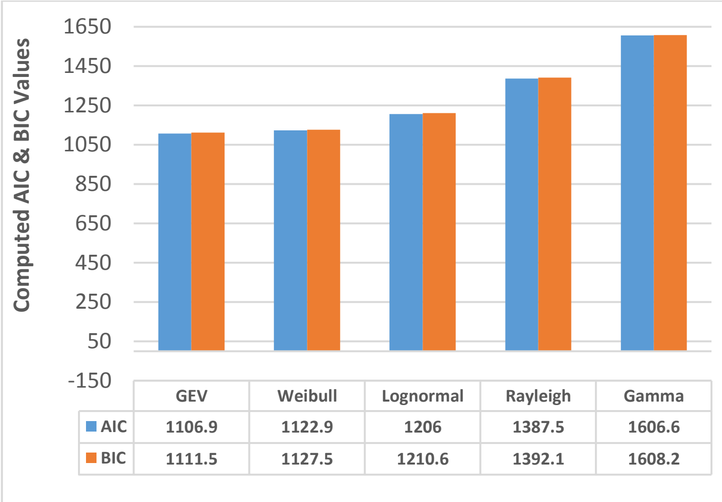

Fig. 8. Fitted PDF of tested five distribution models in L3 (indoor).

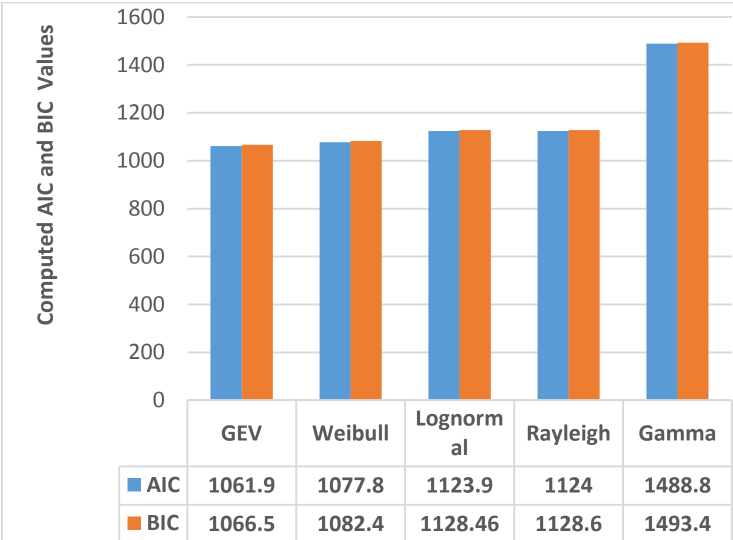

Fig. 9. Computed AIC and BIC values of the tested five distribution models in L1 (outdoor)

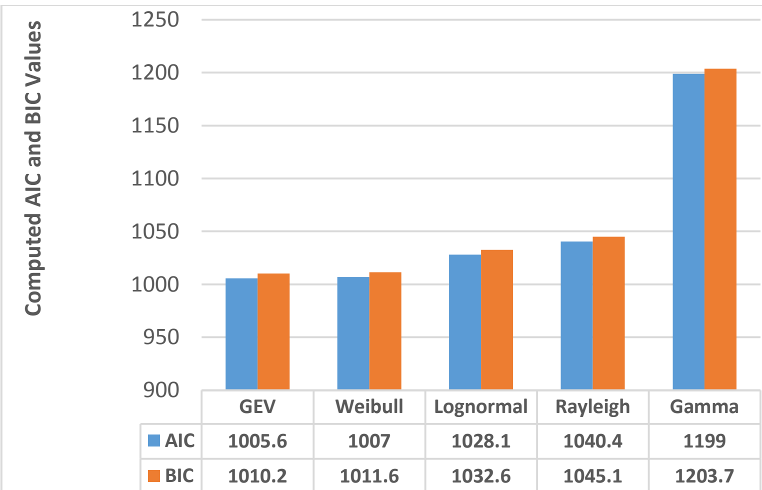

Fig. 10. Computed AIC and BIC values of the tested five distribution models in L3 (outdoor)

Table 2. Summary of computed MLE, AIC and BIC values in L 1 (outdoor)

	GEV	Weibull	Gamma	Lognormal	Rayleigh
Mean	20.48	20.47	20.49	20.69	20.47
Variance	17.00	14.96	26.35	34.30	41.94
MLE	-551.5	-559.4	-601.0	-691.7	-799.8
AIC	1106.9	1122.9	1206.0	1387.5	1606.6
BIC	1111.5	1127.5	1210.6	1392.1	1608.2

Table 3. Summary of computed MLE, AIC and BIC values in L2 (outdoor)

	GEV	Weibull	Gamma	Lognormal	Rayleigh
Mean	24.98	24.98	24.94	24.98	22.33
Variance	11.54	12.89	12.12	12.89	136.2
MLE	-528.9	-536.9	-559.9	-560.0	-742.4
AIC	1061.9	1077.8	1123.9	1124.0	1488.8
BIC	1066.5	1082.4	1128.46	1128.6	1493.4

Table 4. Summary of computed MLE, AIC and BIC values in L3 (outdoor)

	GEV	Weibull	Gamma	Lognormal	Rayleigh
Mean	24.34	24.30	24.32	24.34	21.72
Variance	9.63	8.980	10.44	11.36	128.9
MLE	-500.8	-501.5	-512.0	-518.2	-597.5
AIC	1005.6	1007.0	1028.1	1040.4	1199.0
BIC	1010.2	1011.6	1032.6	1045.1	1203.7

To validate the results presented in this paper, the five probability functions were subjected to GoF tests based on the analysis test using the Kolmogorov-Semirnov selection criteria. Here, the model with the minimum statistic and the lowest rank is selected as the best-fit model. The results in Table 4 revealed that the GEV and Weibull are the most credible distributions in the three study locations. From the results, it is clear that the Kolmogorov-Semirnov Criteria agree with the MLE, AIC and BIC selection criteria. This demonstrates the credibility of our proposed method of finding the most realistic way of selecting the best probability function for the dataset. Similar results are summarized in Tables 2 to 4 for outdoor locations wherein GEV attained the most probable distribution model observed for data acquired in indoor locations. However, the detailed results are not fully highlighted for brevity.

Table 5. Summary of computed Kolmogorov–Semirnov statistics in L1 to L3 (outdoor)

	Location I		Location II		Location III	
	Statistics	Rank	Statistics	Rank	Statistics	Rank
GEV	0.0804	1	0.1494	1	0.1018	1
Weibull	0.1508	2	0.1711	2	0.1269	2
Gamma	0.1754	3	0.1985	3	0.1812	3
Lognormal	0.1862	4	0.2194	4	0.1918	4
Rayleigh	0.3201	5	0.3451	5	0.2444	5

4. Conclusion

Prognostic data processing and analysis is a common stochastic signal processing practice both in temporary and spatial domains and has been an active research area for researchers in science, engineering and related fields. The current work examines the contemporary methods of identifying and selecting the best probability distribution functions to model a stochastic signal propagated over a multipath terrain. The GEV and Weibull functions were selected as the most credible distribution functions for the acquired stochastic SINR data in three different study locations. On the other hand, the Lognormal and Rayleigh functions showed the worst fits. Thus, the GEV and Weibull models could be used in prognostic analysis and detection of the inherent stochastic characteristics of multipath propagated broadband radio frequency signals in typical built-up terrain and proximal environs. The explored approach in this paper can be of useful guide for radio frequency engineers for modelling, designing and management of emerging cellular networks. Future work would employ practical and simulated signal data to test the validity and efficacy of the proposed selection technique of probability distribution functions. Additionally, the field measurement terrain would be extended to cover urban, suburban, rural and forested areas.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interest

The authors declare that they have no conflicts of interest.

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