Statistical Analysis of Reliability in a Real Urban Distribution System

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Abstract

Underground cables are generally used in urban Medium Voltage systems. In the last years, the cable lines appeared to be more fragile than expected, with an increase of the number of faults, especially in the warmest periods of the year with the occurrence of heat waves. This paper, starting from actual data gathered in urban areas, aims to verify the existence of a relation between the number of faults and the temperature increase, to understand the possible limitations in using the classical reliability hypotheses to study the probability distributions of the time between faults. The results indicate the presence of critical periods with remarkable discrepancy between the empirical probability distributions and the exponential distribution used in the classical reliability analysis.

Index Terms

Underground cables, Heat Waves, Medium Voltage, Reliability, Resilience

I. Introduction

Reliability and security were, for long time, considered the two fundamentals properties of the electrical system. However, in recent years, the concept of resilience (or resiliency, as sometimes it is written) is becoming more and more relevant [1]. The conceptual difference between reliability and resilience lies basically on the *types of events* considered and the *impacts* of these events on the power systems. In fact, while reliability aims modeling the occurrence and impacts of low-impact/high-probability faults, resilience considers high-impact/low-probability events. Moreover, reliability is a static feature (one fault only that creates a well-defined lack of supply), while resilience is time-variant [2], because the impact on the system may evolve either due to cascading events or because the phenomenon itself, during its evolution, can interest more extended areas or change in intensity [3] [4].

All the different sectors in which power systems are traditionally divided (i.e., generation, transmission, distribution and utilization) suffer the impact of extreme events, especially weather-related [5]. As a matter of example, extended periods of high temperatures are often linked to drought conditions, which reduce water availability by impacting both hydroelectric generation [6] and fossil fuel-based power plants, particularly due to cooling requirements [7]. High temperatures also affect wind power (by altering wind characteristics) and photovoltaic (PV) output (due to reduced panel efficiency) [6]. Substation equipment, such as transformers, may experience a rise in faults, caused by hot spots and insulation degradation [8]. Moreover,

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since people are sensitive to heat, electricity demand may shift, for instance due to increased air conditioning usage, with subsequent effects on electricity market conditions [9], [10]. In particular, the analysis of the impacts that the extreme weather events have on distribution system is attracting a higher and higher number of researchers [11], as preserving the distribution system infrastructure will become more and more important because of the urbanization trends (in 2050, 6.68 billions of people is estimated to live in cities, about 68% of the worldwide population [12]).

The classical reliability analysis is based on the determination of the frequency and duration of the interruptions, as well as the time between faults, resulting in local and global reliability indicators that can be expressed either in a deterministic way or with probability distributions, for example the cumulative distribution function (*CDF*) [13] [14]. The mean time between failures (*MTBF*) is one of the typical values used to characterize the occurrence of faults in the distribution system [15] [16] [17]. Conceptually, considering the model of repairable components in the distribution system, in the useful life period of all components the Time Between Failures *TBF* follows an exponential probability distribution [18] [19] [20]. The increasing occurrence of heat waves is changing the *TBF* distribution, making the assessment of the effects of faults in the distribution systems more challenging [21].

This paper aims to verify, on a wide set of data gathered from a real urban distribution system, to what extent the hypothesis of exponential distribution of the *TBF* is satisfied both in winter and summer seasons. In particular, the effect of heat waves on urban distribution systems will be checked by comparing the empirical cumulative distribution function (*ECDF*) and the theoretical *CDF* of the *TBF* [22], by deepening the analysis started in [23].

The remainder of the paper is organized as follows. Section II presents the approach used for the data analysis. Section III shows the calculation of the goodness-of-fit to compare different cumulative curves. Section IV reports the simulation results. Section V contains the concluding remarks and indicates directions for future works.

II. Data Analysis

This paper addresses the following three key questions:

1) Is the fault rate influenced by temperature?
2) Is the *MTBF* constant in different periods?
3) Does the *ECDF* of the *TBF* follow an exponential distribution?

On these bases, the framework for evaluating the validity of reliability hypothesis in distribution systems is illustrated in Fig. 1.

The analysis follows these steps:

1) *Historical Data Collection*: The input data set includes details on the fault components, start and end times of the fault, line length, and daily average temperature.
2) *Fault Classification*: The classification of the faults is based on three different dimensions, i.e, year, season, and components. The components include Cable, Cable Joint, and Terminals. For the seasonal classification, Summer consists of May, June, July, August, and September, while Winter encompasses January, February, March, April, October, November, and December. These dimensions are cross-combined to create different combinations, such as (2019, Cable, Summer).
3) *Fault Rate Analysis*: By counting the number of faults of the different combinations and calculating the corresponding fault rate, trends over time are identified. Simultaneously, historical temperature data provides the average annual temperature. The absence of the alignment between fault rate and temperature trends indicates the influence of other factors that should be included.
4) *MTBF Evaluation*: Fault duration is derived from start and end times, allowing annual *MTBF* calculations. If *MTBF* is not constant or approximately similar for different comparable periods, the basic hypotheses of the reliability theory could no longer be applicable.
5) *ECDF Formation*: *ECDF*s are generated for each fault type across different years and seasons. These *ECDF*s not only serve as the basis for the goodness-of-fit tests, but also help visualize the fault rate trends identified in Step 3).
6) *Goodness-of-Fit Test*: In classical reliability studies, the Time Between Failures (*TBF*) is a key metric, and for single and independent faults, its probability distribution is theoretically expected to follow an exponential model. To assess the conformity of the *ECDF* to an exponential distribution, the Kolmogorov-Smirnov (*KS*) test [24] is applied, in which

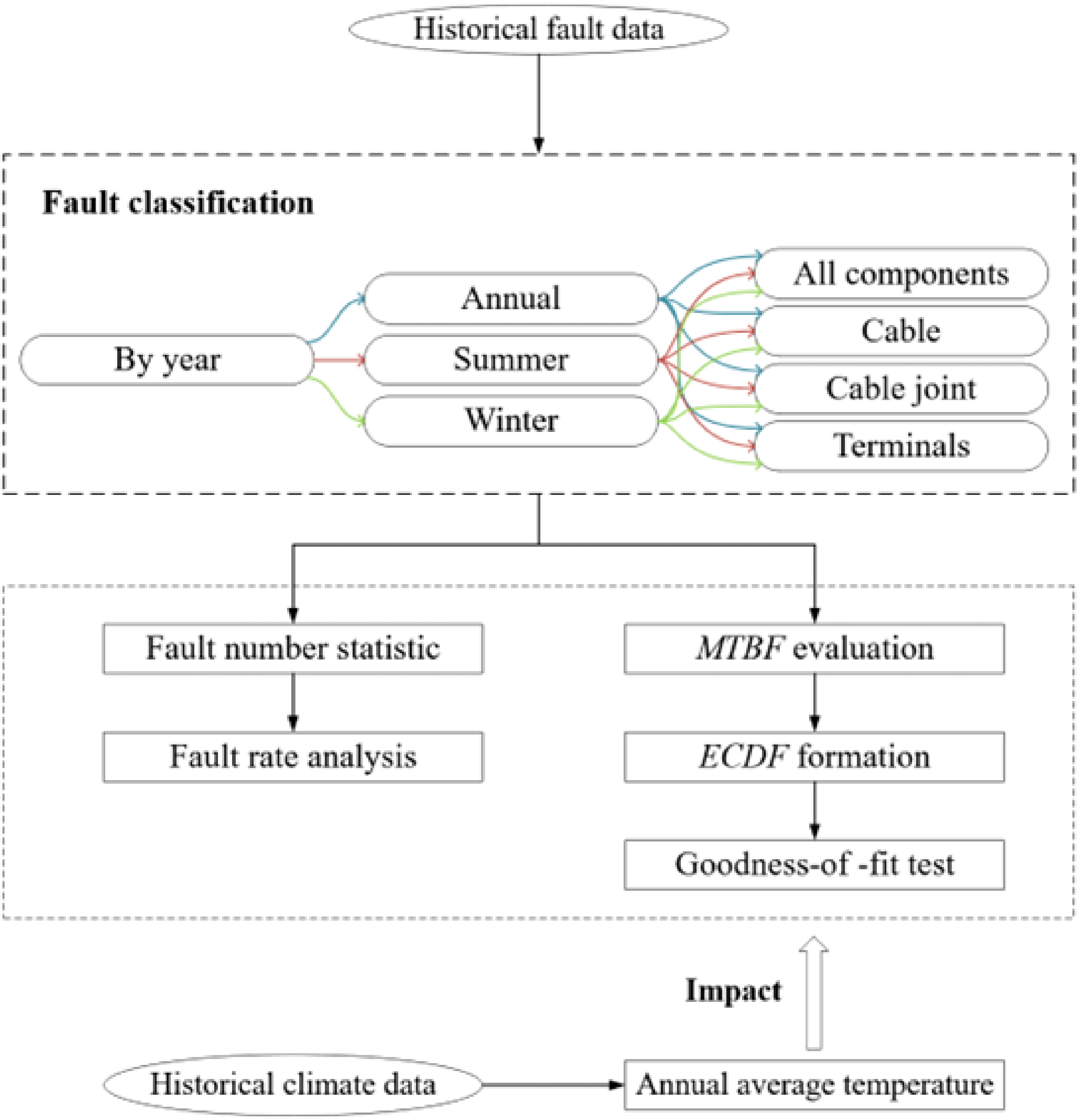

Fig. 1. Analysing flow chart

the critical error threshold is determined based on the chosen significance level. If the hypothesis that *TBF* follows an exponential distribution is not accepted for a given period, the traditional reliability theory may be no longer applicable for that period.

III. Goodness-of-Fit Assessment Model

The goodness-of-fit assessment is conducted using the *KS* test [24], which compares the empirical data against various probability distributions [25] having the same parameter(s) of the *ECDF*. Specifically, the test evaluates the *ECDF* of the *TBF* against the exponential *CDF* with the same mean value, given by:

$$F^{*}(X) = 1 - e^{-\lambda X} \tag{1}$$

TABLE I
NUMBER OF FAULTS FROM 2019 TO 2023

Year	Season	Cable	Cable Joint	Terminals
2019	Summer	51	31	-
	Winter	32	8	-
2020	Summer	111	52	-
	Winter	58	16	-
2021	Summer	84	58	10
	Winter	51	57	11
2022	Summer	121	110	3
	Winter	56	35	20
2023	Summer	168	83	18
	Winter	56	47	13

where λ represents the inverse of *MTBF*, and X is the sample of *TBF*. The *KS* test determines the maximum vertical deviation *D* between the *ECDF* $F(X)$ derived from the observed data and the exponential CDF $F^*(X)$ under test:

$$D = max_X|F^*(X) - F(X)| \tag{2}$$

The error D is then compared to the critical threshold D_{crit}. When the *CDF* being tested is fully defined by its parameters, the critical values D_{crit} are determined from statistical tables based on sample size and significance level [26]. If $D \leq D_{crit}$, the hypothesis that the observations follow an exponential distribution is accepted.

IV. SIMULATION RESULTS

An analysis of the distribution system faults has been conducted using a database referencing the urban distribution system of Turin (Italy), operated by IRETI SpA. Table I presents the number of faults of various combinations, based on all reported faults recorded during the period from 2019 to 2023. As shown in Table I, for Cable and Cable joint faults, the number of faults in summer is significantly higher than in winter, supporting the hypothesis that high temperature contributes to increase the number of faults. In contrast, the number of Terminal faults is considerably lower than the other two types, with no reported incidents in 2019 and 2020. For the summers of 2021 and 2022, the fault numbers were higher than in winter, but in 2023, although the summer fault count was slightly greater than in winter, the difference was minimal — only 5. This indicates that Terminal faults do not follow the same temperature-related pattern observed for Cable and Cable Joint faults.

Using the fault number statistics, the monthly fault rate can be calculated and compared with the corresponding annual average temperature, which has been determined using the method outlined in [27]. This method involves the sum of the maximum and minimum values of all daily temperature records for a given year and the consequent calculation of the average. The daily average minimum and maximum temperatures for Turin from 2019 to 2023 are provided by Arpa Piemonte in [28]. As shown in Fig. 2, the annual average temperature (red bar graph) from 2019 to 2023 remained relatively stable, with a slight dip in 2021 (14.36 °C), followed by a sharp increase to 15.7 °C in 2022. Meanwhile, the fault rate (blue line chart) has been steadily rising from 2019 to 2023, although the growth rate slowed significantly in 2021, when the annual average temperature was at its lowest. This suggests that temperature is one cause influencing the fault rate, with aging being likely another key contributing factor.

The *TBF* is calculated based on the start and end time of the faults: thanks to it, it is possible to calculate the *MTBF* across various seasons and on an annual basis.

A. Analysis of the MTBF Without Component Distinction

The annual *MTBF* is presented in Fig. 3. The data reveals that, without considering the component type, the *MTBF* follows a generally constant but gradually decreasing trend from 2019 to 2023, declining from 2.25 days in 2019 to 0.93 days in 2023. In particular, there is no data for Terminals before 2021.

By considering the summer period in different years (Fig. 4), the *MTBF* for all components shows a trend going from 1.76 days in 2019 to 0.55 days in 2023. By comparing Fig. 4 with Fig. 3, *TBF* is influenced by temperature — higher

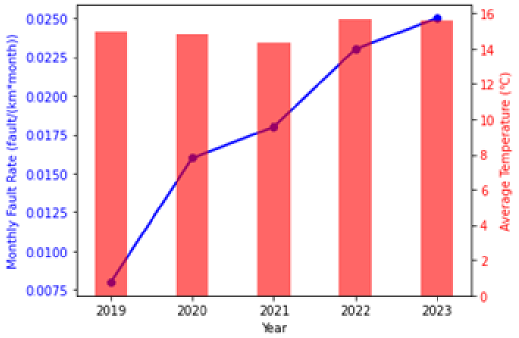

Fig. 2. Monthly Fault Rate vs. Average Temperature (2019-2023)

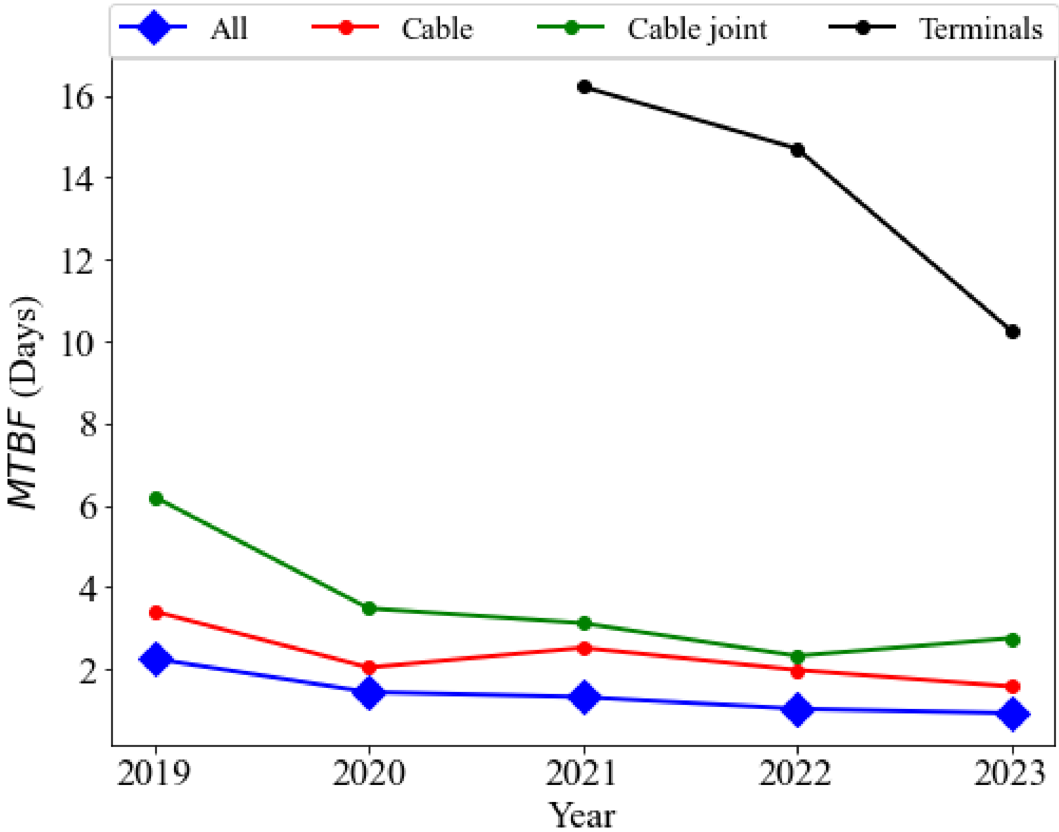

Fig. 3. *MTBF* by different components.

temperatures in summer result in a shorter *TBF* compared to the winter season (Fig. 5). Moreover, *TBF* could be affected by aging effects, with an overall shortening trend as time progresses.

B. Terminals, Cable and Cable Joints

For Terminal-type faults, the annual *MTBF* ranges from 16.20 days in 2021 to 10.26 days in 2023 (Fig. 3), and the summer *MTBF* is 10.64 days in 2021 and 4.34 days in 2023, while in 2022 there is the high value of 25.81 days (Fig. 4) that however refers to three faults only (Table I), and the winter *MTBF* varies from 17.64 days to 32.42 days (Fig. 5).

By comparing these fault types across all seasons, it becomes clear that, regardless of the time frame (annual, summer, or winter), Terminal faults have the longest *MTBF*, followed by Cable Joints; hence, Cables have the shortest *MTBF*. This pattern is linked to the frequency of fault occurrences: more frequent faults result in a shorter overall *MTBF*.

Cable and Cable Joint in summer exhibits the slowest *MTBF* change over time (Fig. 4), with the winter *MTBF* showing instead a significant fluctuation over the years (Fig. 5).

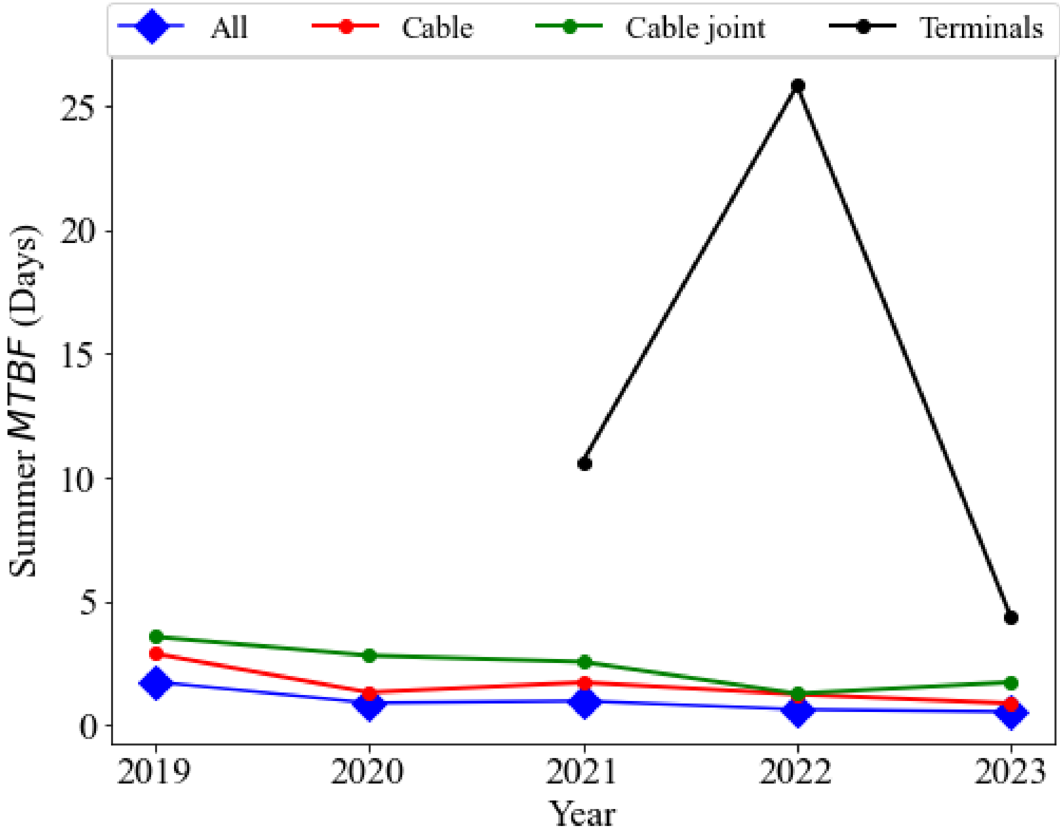

Fig. 4. Summer *MTBF* by different components.

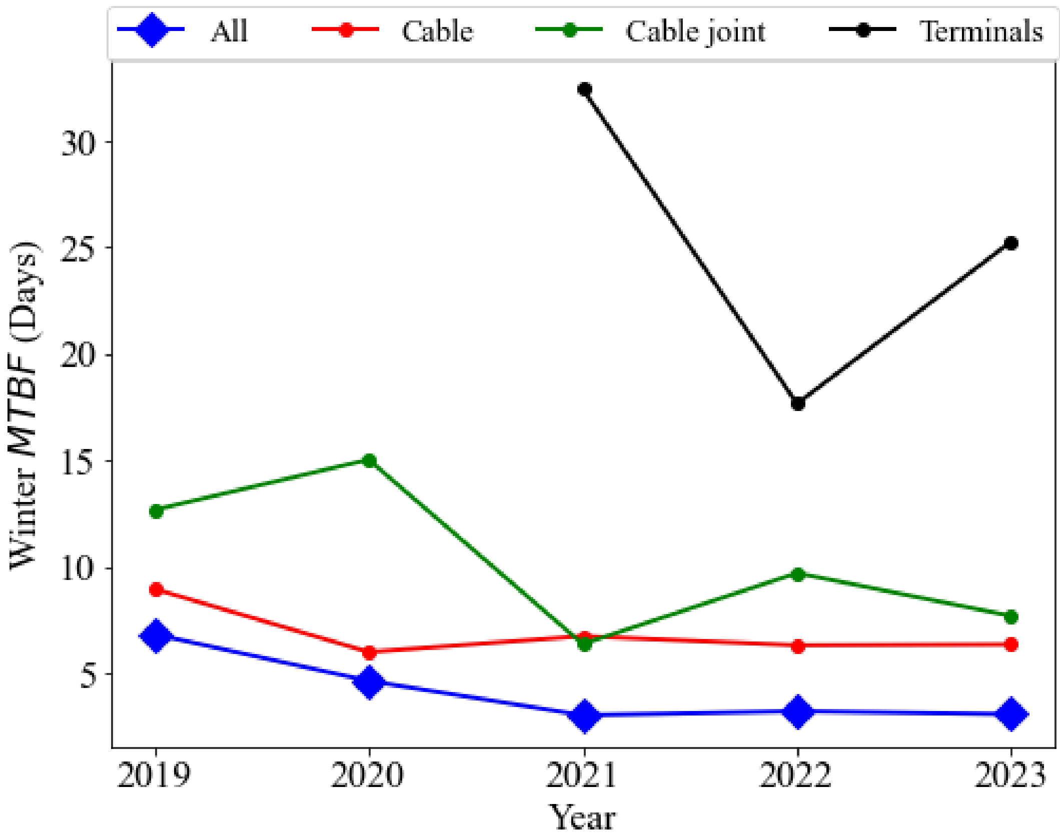

Fig. 5. Winter *MTBF* by different components.

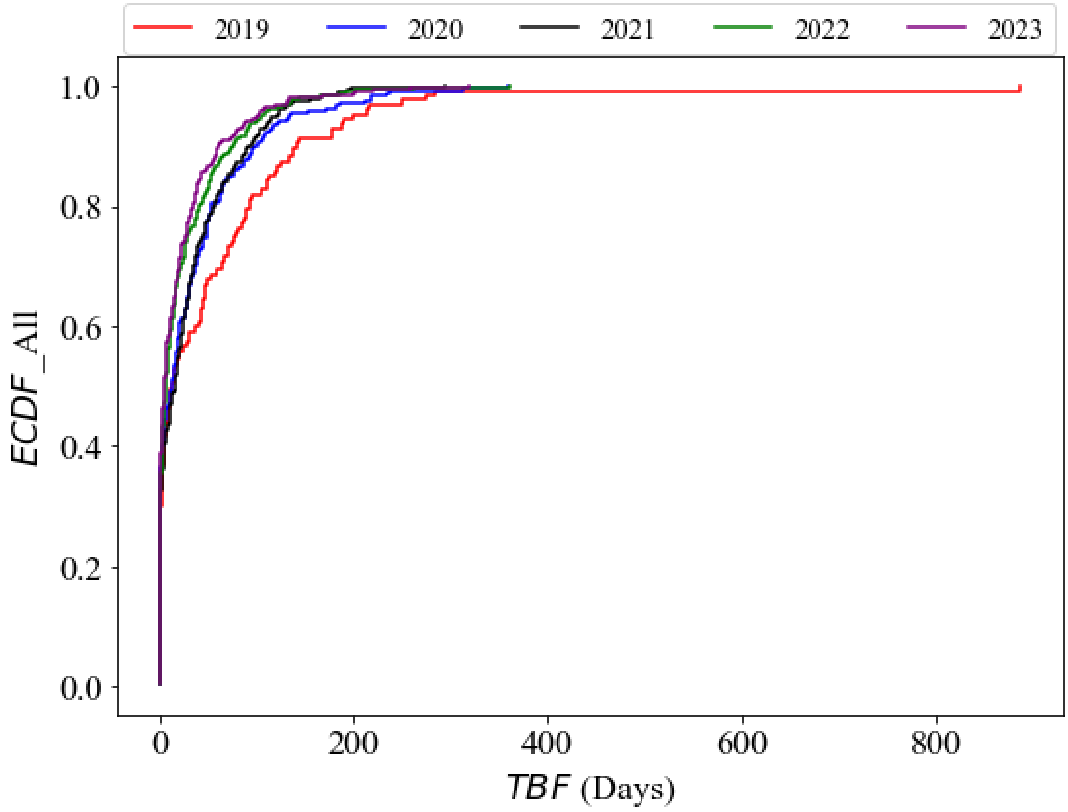

Fig. 6. Annual *ECDF* of all components.

C. ECDF Construction

The *ECDF* can be constructed based on the *MTBF*. Fig. 6 and Fig. 17 display the *ECDF*s for different combinations of year, season and components. From an annual perspective, as shown in Fig. 6, the best performance was found in 2019, followed by 2020, while 2023 showed the poorest performance (the curve on the left-hand side). The key factors contributing to this are: *i*) the overall *TBF* in 2023 is shorter, *ii*) the maximum *TBF* in 2023 is significantly lower than in 2019, and *iii*) faults are much more common in 2023. For both Cable and Cable joints, a similar trend is observed, as shown in Fig.7 and Fig. 8. For Terminals, the performance gradually declined from 2021 to 2023, with the overall *TBF* consistently decreasing and faults becoming more frequent, even though the maximum *TBF* value increased during the years, as depicted in Fig. 9. However, the maximum *TBF* value refers to a single point and as such is not significant to establish a trend. In summer, when the component type is not considered, the *ECDF* performance from best to worst is as follows: 2019, 2021, 2020, 2022, and 2023, as shown in Fig. 10. Compared to Fig. 6, the *ECDF* performance does not consistently decline over time. This could be attributed to the relatively lower temperatures in 2021, which resulted in better performance compared to 2020. Cable-type faults follow a similar trend, as shown in Fig. 11. However, this pattern does not apply to Cable joints and Terminals, as seen in Fig. 12 and Fig. 13.

In winter, when the component type is not considered, the *ECDF* shows the best performance in 2019, followed by 2020, with minimal differences between the other years, as shown in Fig. 14. For Cable-type faults, the *ECDF* performs as its best in 2019, with little variation among the other years, as depicted in Fig. 15. The pattern for Cable joints, shown in Fig. 16, is like the one in Fig. 14. For Terminals, the *ECDF* performs best in 2021, with little difference between 2022 and 2023, as shown in Fig. 17.

D. Goodness-of-Fit Test

Finally, a goodness-of-fit test is performed on each combination. The significance level of the *KS* test was set to 0.01. The accepted combinations are shown in Table II. The results indicate that the accepted outcomes in the test are limited to Cable joints and Terminals. For Terminals, the system has shown consistent reliability from 2021 to 2023, both in summer and winter, suggesting that the summer high temperature has no impact on their performance. For Cable joints, while the

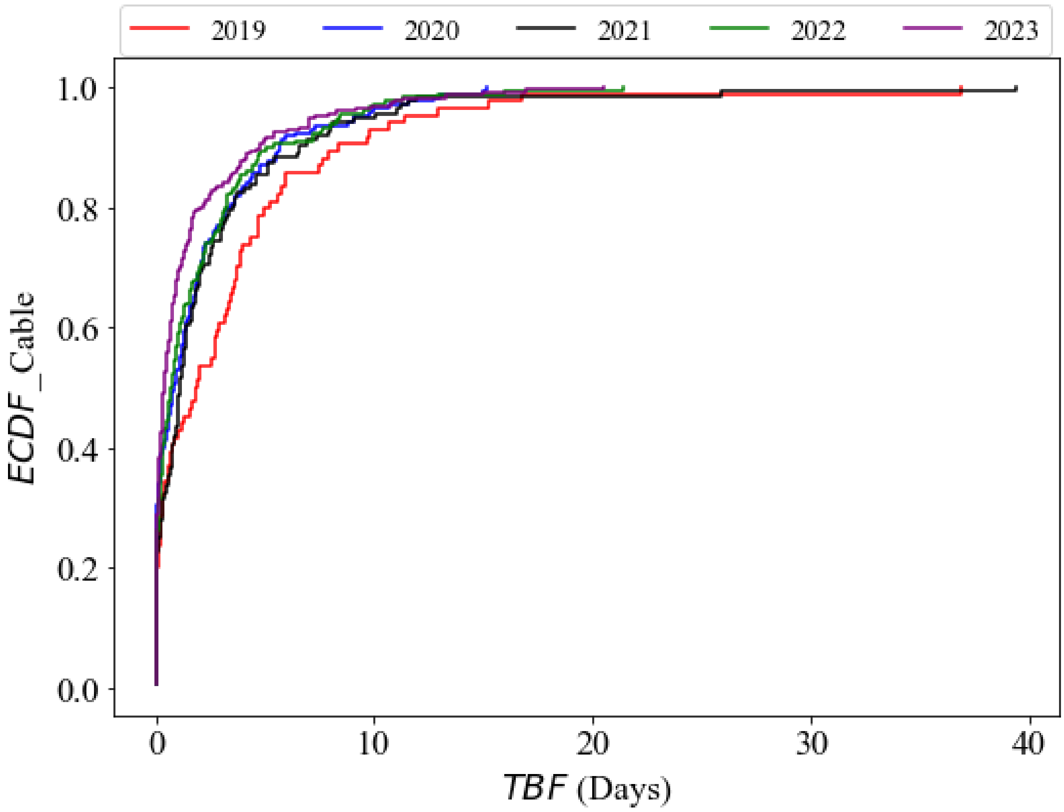

Fig. 7. Annual *ECDF* of Cable.

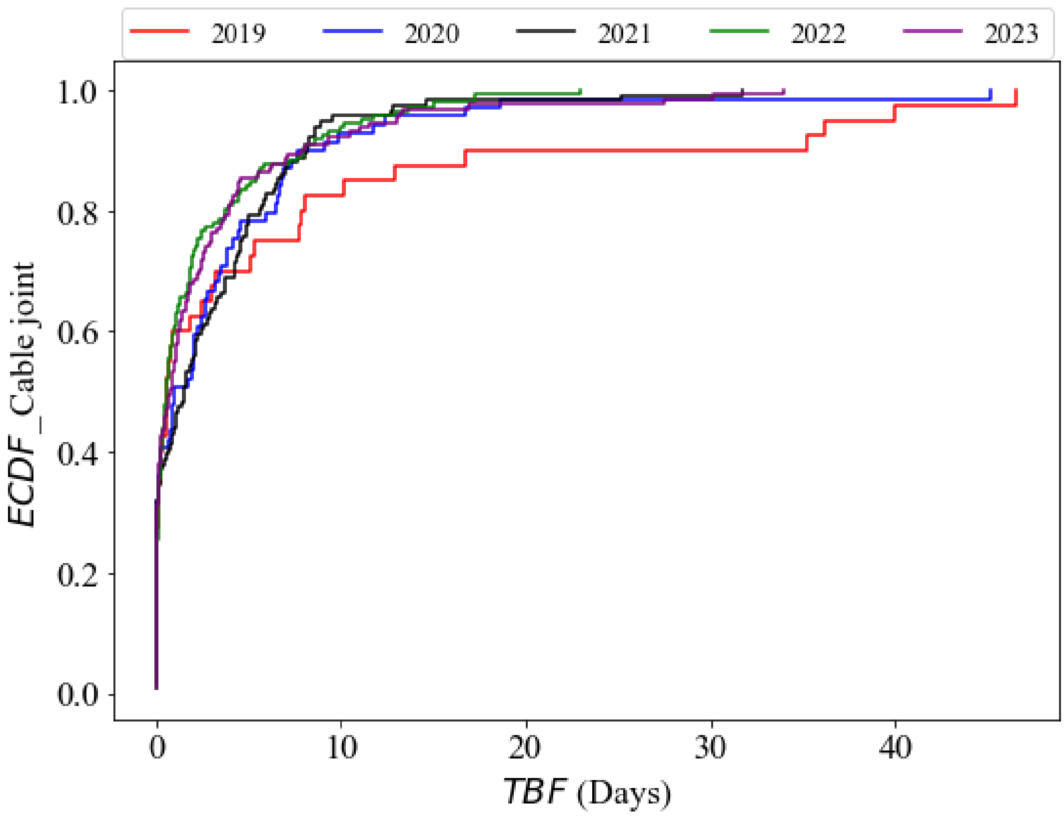

Fig. 8. Annual *ECDF* of Cable joint.

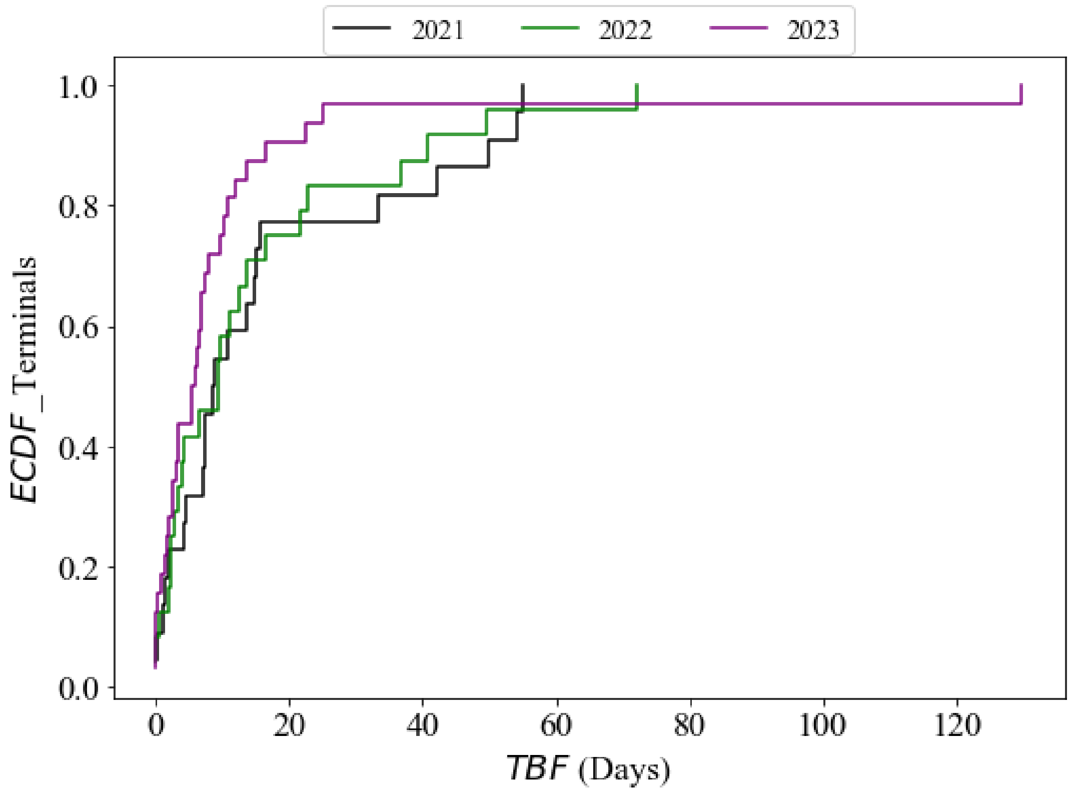

Fig. 9. Annual *ECDF* of Terminals.

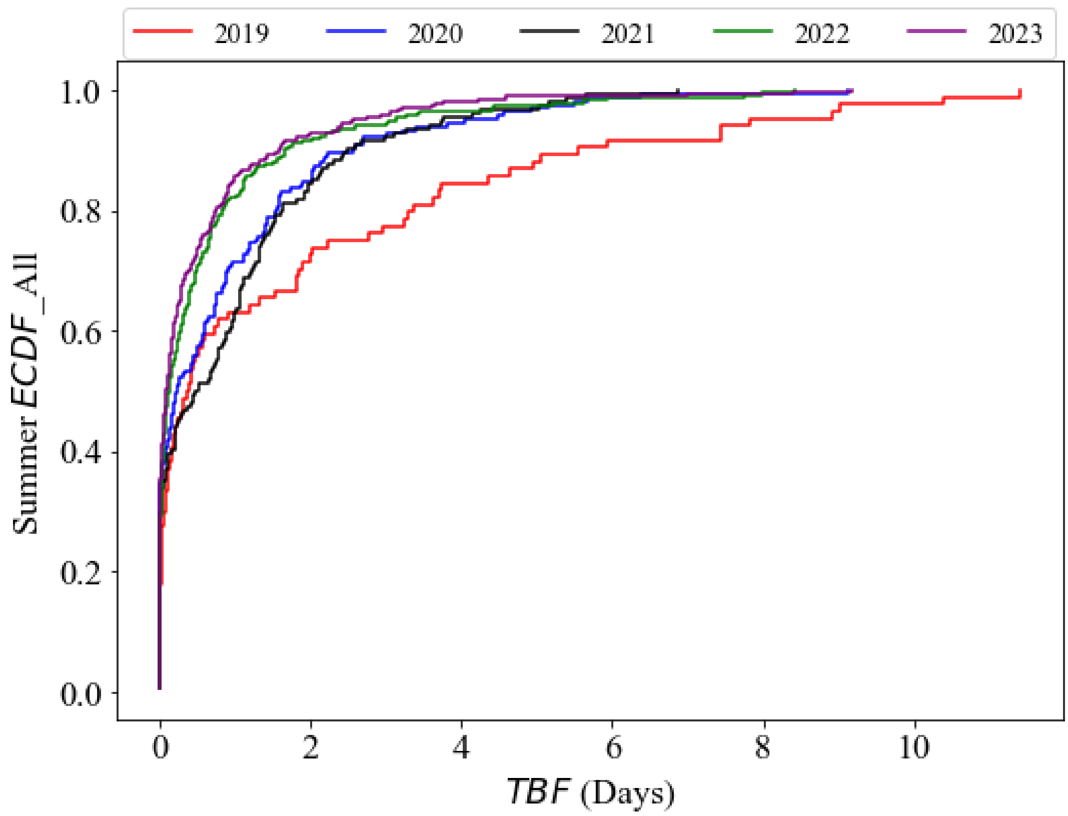

Fig. 10. Summer *ECDF* of all components.

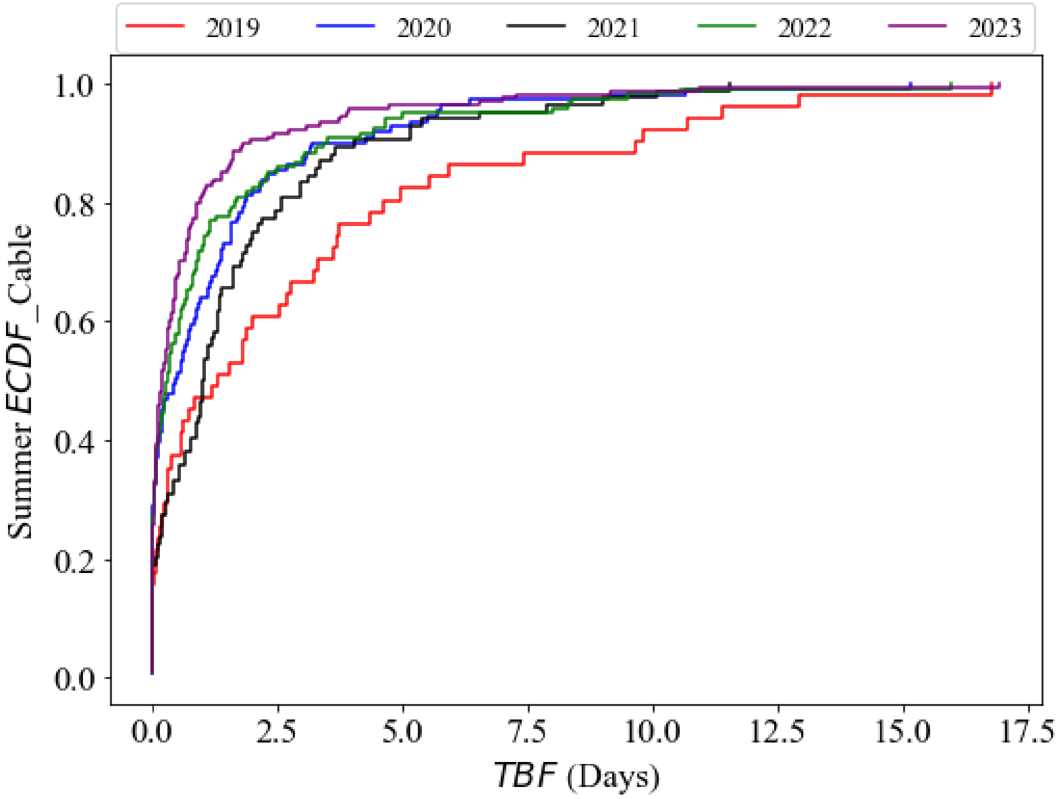

Fig. 11. Summer *ECDF* of Cable.

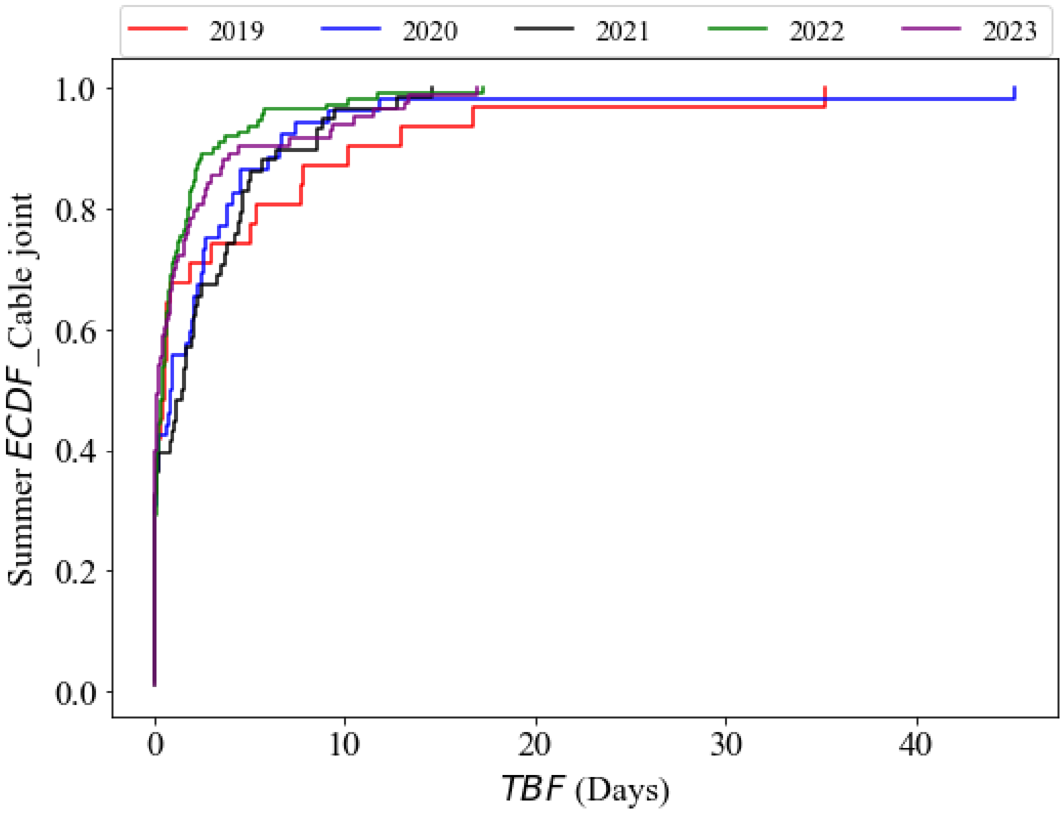

Fig. 12. Summer *ECDF* of Cable joint.

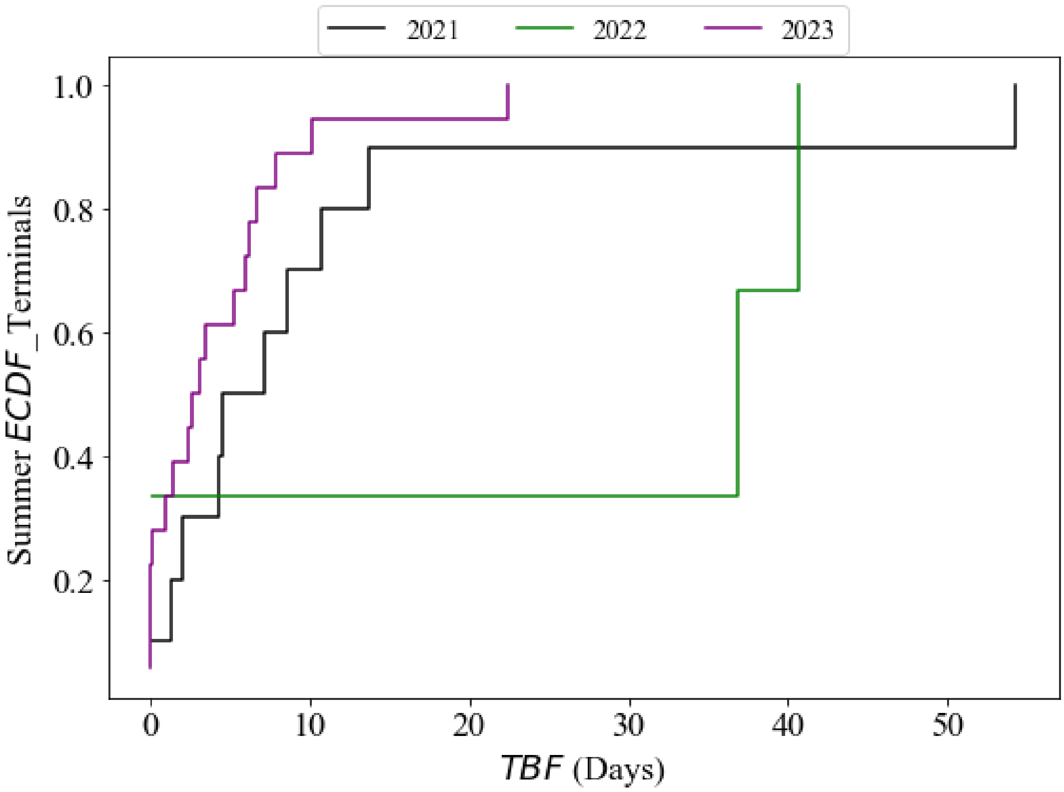

Fig. 13. Summer *ECDF* of Terminals.

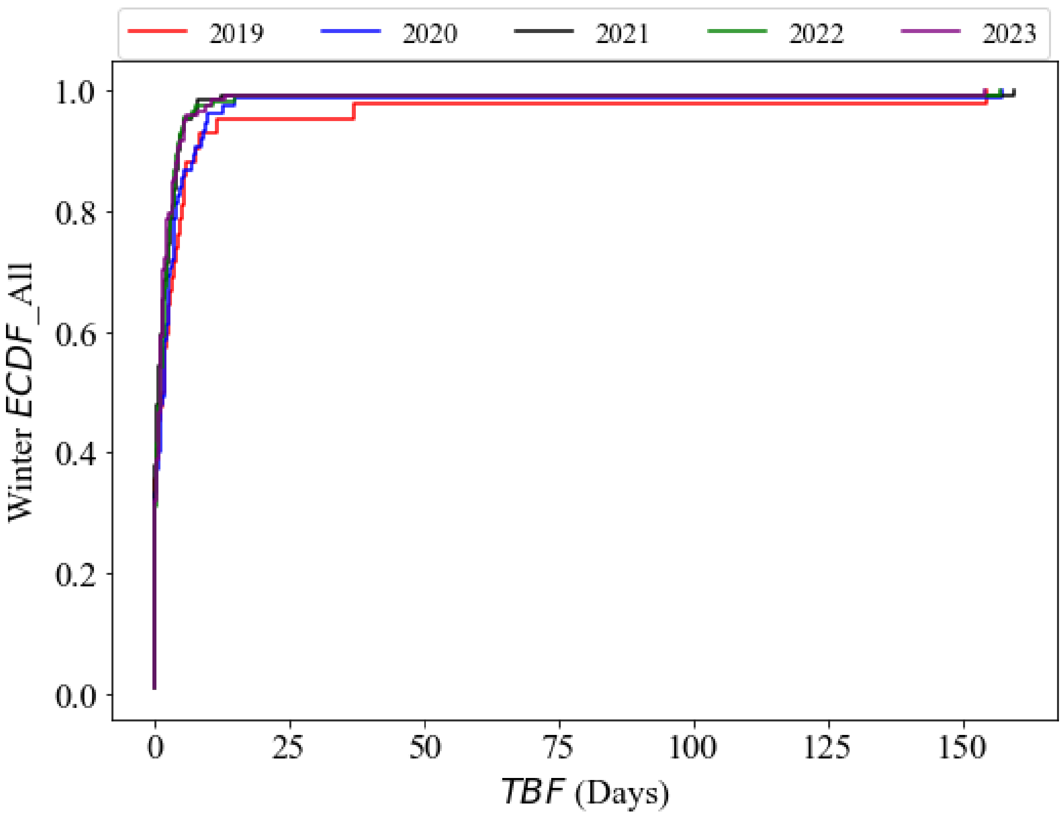

Fig. 14. Winter *ECDF* of all components.

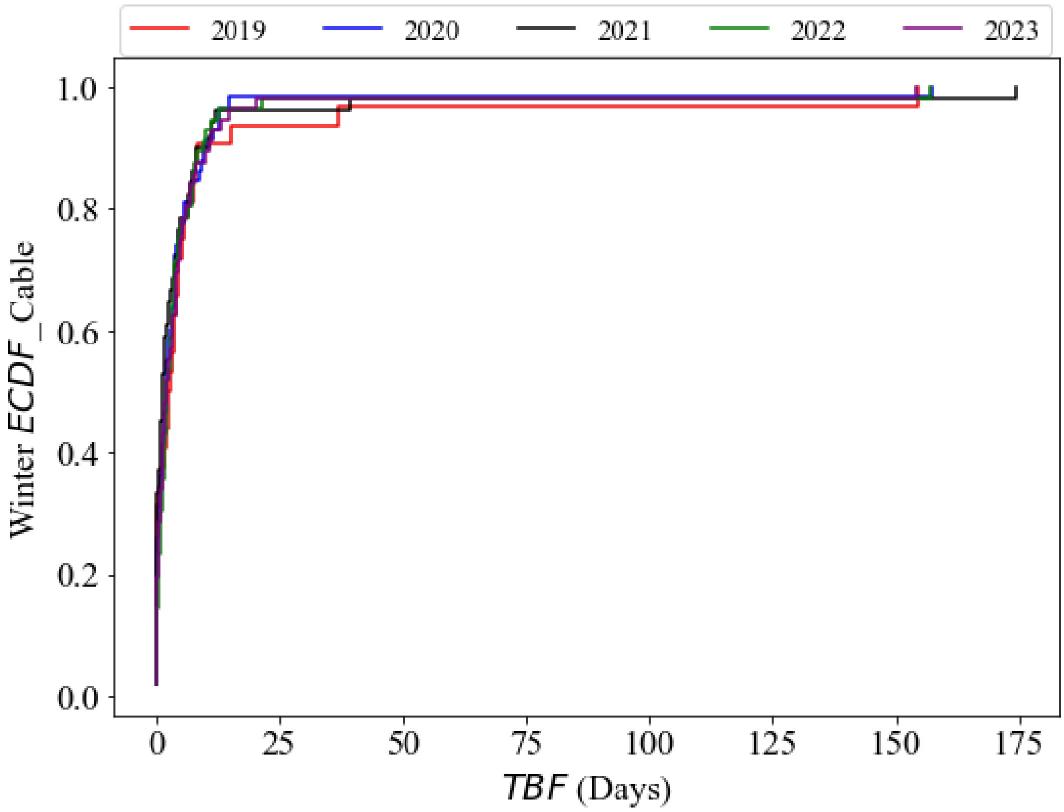

Fig. 15. Winter *ECDF* of Cable.

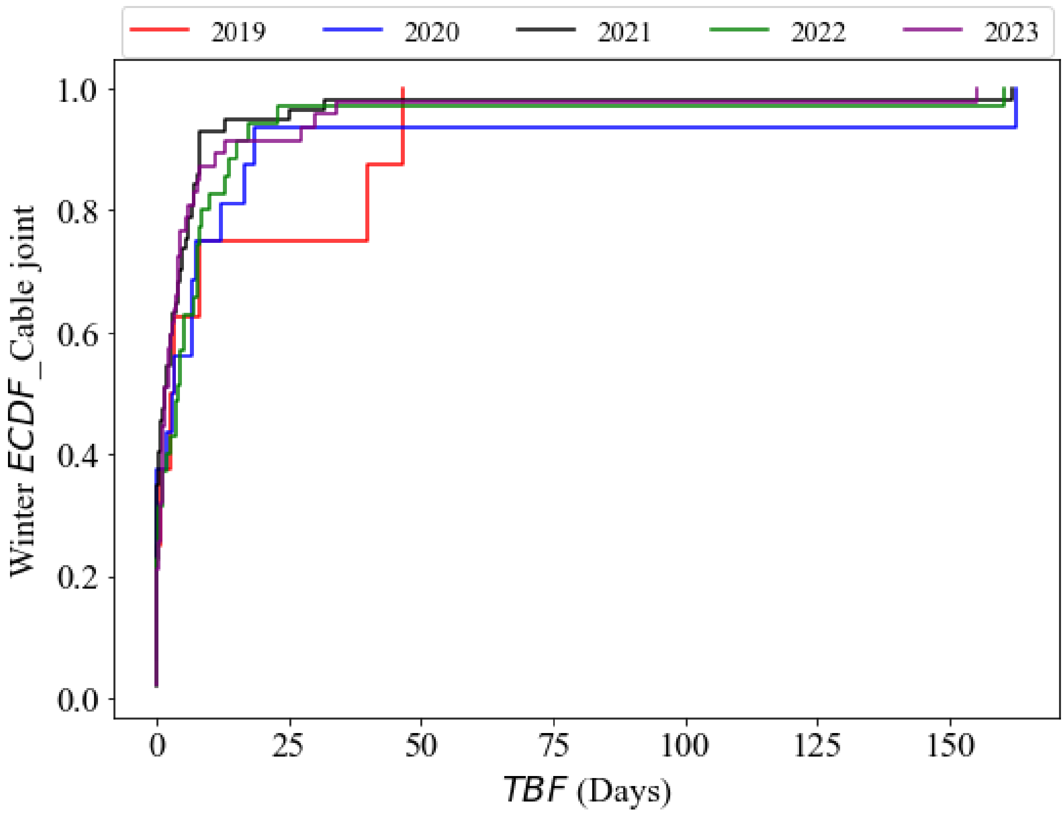

Fig. 16. Winter *ECDF* of Cable joint.

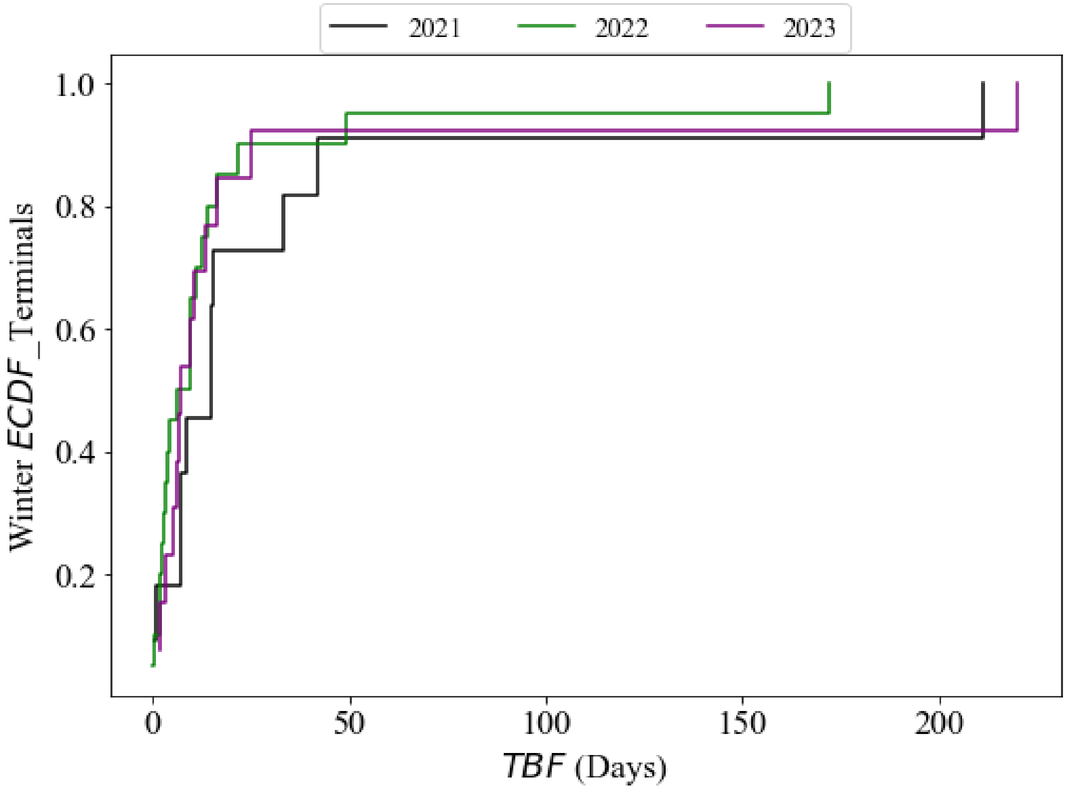

Fig. 17. Winter *ECDF* of Terminals.

summer of 2020 should theoretically have been marked as “not accepted”, it was instead “accepted”. These discrepancies do not correlate with the average temperatures of the corresponding years: hence, this indicates that Cable joints do not fully align with existing theoretical expectations. Regarding Cable, all winters from 2019 to 2023 were marked as “not accepted”, indicating other factors influencing Cable faults during the winter months.

TABLE II
ACCEPTED RESULTS OF GOODNESS-OF-FIT ASSESSMENT

Combination	D value	Critical value
2021 Terminals	0.1275	0.3611
2022 Terminals	0.117	0.3443
2023 Terminals	0.193	0.305
2020 Cable joint-Summer	0.1932	0.2584
2021 Terminals-Summer	0.1763	0.489
2022 Terminals-Summer	0.6136	0.9293
2023 Terminals-Summer	0.1162	0.4042
2019 Cable joint-Winter	0.3645	0.5758
2020 Cable joint-Winter	0.3959	0.4042
2022 Cable joint-Winter	0.2295	0.2997
2021 Terminals-Winter	0.303	0.5418
2022 Terminals-Winter	0.2743	0.3706
2023 Terminals-Winter	0.3943	0.4677

V. CONCLUDING REMARKS

This research aimed at investigating to what extent the classical reliability hypothesis are applicable to distribution system faults. A framework was developed that includes fault rate analysis, *MTBF* evaluation, *ECDF* formation, and goodness-of-fit test. The results, based on real data collected between 2019 and 2023 on the number of faults in components such as Cables and Cable joints, suggest that high temperatures actually contribute to fault occurrence. This is instead different for the Terminals. Regarding the fault rates, temperature is identified as one of several factors influencing fault occurrence, with aging emerging as another significant contributor. This also holds for the *TBF*.

Finally, the goodness-of-fit test indicates that high summer temperatures have a small impact on the reliability performance of Terminals, while these temperatures are a quite important factor for Cables and Cable joints.

This study uses the exponential distribution as a baseline model. Future research will explore more sophisticated statistical methods, including the Anderson-Darling test, survival analysis, and hazard modelling. Additionally, predictive modelling techniques—such as regression analysis and time-series forecasting—will be employed to quantify the relationship between ambient temperature and failure rates.

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