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A fitting procedure for probability density functions of service restoration times. Application to underground cables in medium-voltage networks

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ABSTRACT

Distribution companies have the responsibility to provide a quality service to their customers, according to the existing regulation. Reliability issues, such as power outages, are registered in databases for a quantitative evaluation of this quality. This paper uses one of these historical records to make a statistical analysis of service restoration times, applied to the particular case of underground cables in medium voltage networks. An algorithm is proposed to fit the raw data to the probability density functions typically used in reliability analysis. The best-fitted distribution is determined in each case according to the information provided by a set of goodness-of-fit tests. Different groups are considered for the elements of the systems, concerning their functionality and voltage level. The presented procedure is applied to an electrical network with more than 350 feeders. Results have been obtained globally, showing that the observed service restoration time is lower than the estimated maximum limit in 98.00% of cases. The probability functions provided by the proposed algorithm can be used to improve the accuracy of the reliability models for the electric power system.

1. Introduction

Reliability of power supply is an important concept related to the quality of the service provided by electrical utilities, [1]. In this context, power outages, either momentary or sustained in time, must be correctly characterized in terms of frequency and duration. Specifically, the interruption duration is deeply analyzed by distribution system operators (DSOs) to determine the so-called power availability of the system. Although major failures are rare events in electric power systems, especially with the arising of smart grids, [2], their effect on consumers might be quite severe. For this reason, power restoration plans are required, [3,4].

A customary way to quantify the reliability of electrical networks is based on the use of international key performance indicators (KPIs), dependent on the durations of different system failures and their frequencies [5,6]. An example of a KPI is the well-known system average interruption duration index (SAIDI). These indices are also used by the concerned authorities to economically penalize the distribution companies.

To adequately determine the previously mentioned KPIs, historical records are typically used to statistically characterize some parameters related to the reliability of the system [7–9]. Failure rate (FR) and time to repair (TTR) are the most reported among these parameters, given their importance in reliability assessments. The first one concerns the number of times that a particular element of the system fails in a specified period. Regarding TTR, this parameter is directly related to the duration of permanent faults in the network, when topological reconfiguration is not possible, for example, in rural areas with a radial configuration. In the case of meshed networks, the duration of power outages is typically denoted as time to restore the supply (TTRS), [10]. In the context of the remarkable amount of data included in the historical records used by DSOs, several techniques are presented in [11] and [12] to deal with this information, such as those based on artificial intelligence (AI), used to predict the behavior of power systems with a high penetration of renewable energy sources.

Regarding the availability of historical records, some publications indicate a shortfall in data from medium voltage (MV) networks, compared to high voltage (HV) levels [13,14]. Furthermore, references [7] and [15] report a lack of research related to service restoration procedures using real data. In several analysis, such as those presented in [16] and [17], the values considered for the FR and mean time to repair (MTTR) are taken from the limits established by grid codes, giving evidence of a lack of information in this regard, since these values do not

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List of Abbreviations

A-D	Anderson-Darling
CDF	Cumulative density function
DSOs	Distribution system operators
FR	Failure Rates
GoF	Goodness of fit
KPI	Key performance indicator
K-S	Kolmogorov-Smirnov
MV	Medium voltage
OPI	Oil-paper insulation
PDF	Probability density function
SRT	Service restoration time
TTI	Thermoplastic and thermosetting insulated cable
TTR	Time to repair
TTRS	Time to restore the supply

represent the actual reliability parameters. In addition, these values of FR and MTTR present remarkable variability with the network topology, operating conditions and the characteristics of the involved elements, [18]. Such variations should be considered by the estimation method, as that described in this paper.

As stated previously, the reliability-related parameters presented are used to obtain the KPIs of the network under evaluation, [19], and also to improve these quality indices, as proposed in [20]. In addition, these parameters are involved in a wide range of applications, such as the implementation of preventive and corrective action plans for individual elements of the system, [21], protection design, [22], or reconfiguration modeling in radial networks, [23].

Regarding service restoration, reference [24] presents a literature review from 2006 to 2016, showing that recent research is focused on black-start, network reconfiguration and load restoration using emerging technologies.

For reliability assessment in electric power systems, Markovian models and Monte Carlo simulations are typically used, [25]. These techniques require specific values of the FRs, which are customarily modeled using a bathtub curve, as in [26–28] and [29], so that this parameter is taken as nearly constant during the component lifetime, [30,1]. In the particular case of the time to failure (TTF), if constant FRs are considered, TTF follows an exponential distribution, as can be found in [29]. However, it is shown in [31] that, according to the Laplace test, unscheduled FRs may not be considered as constant. Other reliability parameters, such as TTR or TTRS, are assumed to be random variables, represented by their corresponding probability density functions (PDFs), [9,32,33], used in the corresponding Monte Carlo simulations. The use of PDFs to statistically characterize reliability parameters, such as the SRT, is justified in reference [34], where the estimation of the system KPIs is addressed.

At the industrial level in general, [35], and particularly in reliability of electric power distribution, [1], several PDFs are used, such as normal, lognormal, exponential, gamma, and Weibull. For example, exponential, Weibull, Rayleigh and gamma distributions are considered in [17] to be the most suitable to calculate time to failure and TTR values for different elements of the system, based on historical records and statistics from DSOs. However, in reference [17] none of the considered PDFs provided successful results in the estimation of KPIs. The log-logistic distribution, which is described in [36], is also used to model and analyze component lifetimes and FRs, [37,38].

This paper presents a methodology to fit real data, extracted from databases provided by DSOs to an appropriate PDF which can be subsequently used in reliability models of the electrical network. In this work, the proposed procedure is applied to statistically characterize service restoration times (SRTs) of underground cables in MV networks, considering aggregated and disaggregated groups of elements. The obtained results are finally validated in a MV network with 350 feeders. The main contributions of this work are summarized below:

- The proposed technique deals with existing outliers in the database.
- Best fitted PDFs are obtained according to statistical information exclusively.
- Confidence intervals can be obtained for the SRTs, which would not be possible if the sample mean is used.

The rest of the paper is arranged as follows: Section 2 describes how the data from the historical record are treated and Section 3 presents the proposed fitting algorithm. The obtained results and their validation are respectively included in Sections 4 and 5. Section 6 is devoted to a discussion on the applicability of the proposed technique, while the conclusion of the paper is presented in Section 7.

2. Data pooling

Information about incidents in electrical networks is collected by the corresponding utilities and saved in databases, as that used in this paper. Data are extracted from a Spanish MV network, the time period being from 2001 to 2013. Specifically, this work is focused on SRTs of unscheduled permanent faults in 15 kV and 20 kV underground cables. In this context, reference [1] states that the minimum time threshold to define a permanent interruption depends on the territory. In the particular case of the Spanish regulation, faults lasting more than 3 min are considered as permanent interruptions, used for the calculation of KPIs. For this reason, faults with a duration lower than 3 min are removed from the database. Each faulty element is registered in the database used in this work, so that interruptions originated in underground cables are clearly identified. For the network under study, interruption causes and FRs are reported in [31]. Outages related to customer installations are not included in the database.

Two different approaches are considered for processing the raw data used in this work. First, the whole population of SRTs is taken as a unique aggregated group, namely 15/20 kV. For the second approach, the components of the system are considered independently, as disaggregated groups, in order to estimate the PDF of the SRT for each one of them. Regarding the latter approach, in the event of data deficiency or variability in the population, [39], a relationship between certain groups must be established to achieve a representative sample. For this purpose, the samples in 15 kV and 20 kV are grouped according to the type of insulation and joints, as stated in [31]. The resulting groups considered in this paper for the calculation of disaggregated SRTs are thermoplastic and thermosetting insulated cable for 15 kV (TTI15 kV), thermoplastic and thermosetting insulated cable for 20 kV (TTI20 kV), oil-paper insulation for 15 kV (OPI15 kV), oil-paper insulation for 20 kV (OPI20 kV), slices in 15 kV (Slice15 kV) and slices in 20 kV (Slice20 kV).

The configuration of the network under study is weakly meshed, radially exploited, including a circuit breaker at the head of each MV feeder. In case of service interruption, the SRT can be reduced by means of a conventional service restoration strategy, [33], with the corresponding switching operations, [13]. With the previous considerations, the SRT includes the time for the location and isolation of the fault, together with the time to restore the power supply through alternative paths. For each service interruption, the SRT is calculated using the database information and the following expression, as used in [6]:

$$SRT = RTS - STS \tag{1}$$

where RTS corresponds to the timestamp of the moment when the service of the last customer is restored, and STS refers to the timestamp of the instant when the supply is interrupted.

3. Proposed algorithm

Once aggregated and disaggregated SRTs are obtained according to Eq. (1), a set of PDFs is fitted to the resulting data. These PDFs are used to obtain the expected values of the restoration times and confidence intervals for this variable, which cannot be derived from raw data. Additionally, the fitted functions might be included in reliability analysis based on Monte Carlo simulations to estimate the KPIs of the system and make the economic assessment of their possible violations. In this work, the considered distributions are exponential, gamma, Weibull, lognormal and loglogistic. To assess each of these fits, two goodness of fit (GoF) tests are used: Kolmogorov-Smirnov (K-S) and Anderson-Darling (A-D), [40].

For some groups, none of the GoF tests were satisfied for any of the PDFs considered because of the remarkable differences between observed and estimated data, especially for long SRTs with low-probability events. To overcome this problem, an algorithm is proposed to improve the fitting process. With this technique, the low-probability events are detected and removed iteratively, until one or more GoF tests are satisfied for each PDF. These removed events might be associated to lack of accuracy of the considered PDF, arise of rare events, or even to errors in the recording of the involved timestamps. Finally, the best-fitted distribution is taken as that with the lowest number of removed events. Once the PDF is selected, the number of bins and their width in the representation of the resulting histograms are chosen according to the p-value provided by a chi-squared ($\mathscr{X}^2$) test, [41].

Fig. 1.b illustrates an example where the proposed algorithm is applied to the aggregated group 15/20 kV. In this case, the loglogistic distribution resulted in the best-fitted PDF. For comparison purposes, Fig. 1.a shows the histogram of the 15/20 kV group before the algorithm is applied, together with the fitted loglogistic PDF. It can be noticed in the zoomed plot that data are better fitted after the proposed algorithm is applied, especially in the upper tail of the PDF, where unacceptable differences are obtained between observed and estimated SRTs (more than ten hours). In the case of Fig. 1.a, neither the K-S nor the A-D GoF tests are satisfied.

The steps of the proposed algorithm, as summarized in the flowchart of Fig. 2, are described below:

1. Pre-processing. The values of SRTs calculated using the raw data and Eq. (1) are pre-processed in order to remove unrealistic values, which might be associated to recording errors, such as negative SRTs. In the database considered in this work, no values are removed in the pre-processing.

2. Data pooling. Creation of the different groups for the disaggregated analysis of SRTs with the pre-processed values from the previous step. Regarding the aggregated analysis, the whole set of pre-processed data is considered as a single group.

3. PDF fitting. For each group:

3.1. For each PDF considered in this paper (parallel branches in the flowchart):

3.1.1. K-S GoF test. After fitting the PDF, the K-S test is calculated considering a significance level of 0.05. The null hypothesis of this test, h, assumes no difference between the observed and the theoretical distribution.

- If the null hypothesis is rejected ($h = 0$ in the flowchart), the probability of each event in the group is separately calculated using the fitted PDF.
- The event with the lowest probability is removed iteratively, increasing the number of removed events (NRE) of the corresponding PDF, namely $\mathrm{NRE_{LL}}$, $\mathrm{NRE_{G}}$, $\mathrm{NRE_{W}}$, $\mathrm{NRE_{E}}$, $\mathrm{NRE_{LN}}$ for log-logistic, gamma, Weibull, exponential and lognormal, respectively.
- This process is repeated until the null hypothesis of the K-S is accepted ($h = 1$ in the flowchart).

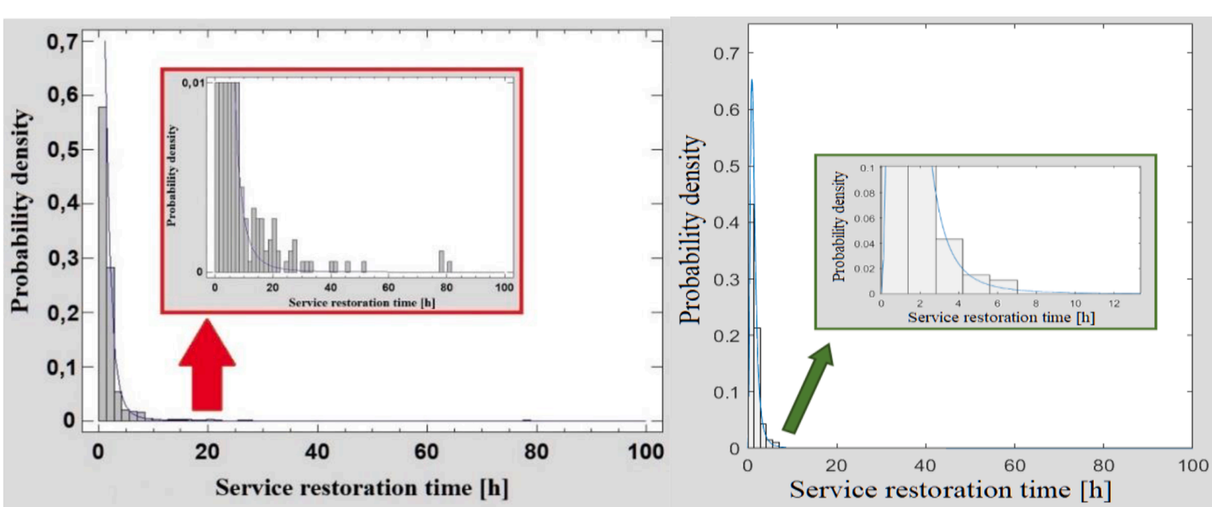
3.1.2. A-D GoF test. After the null hypothesis of the K-S test is accepted, the A-D test with a 0.05 significance level is computed.

- As for the previous GoF test, if the null hypothesis is rejected ($h = 0$), the probability of each event in the group is calculated separately using the fitted PDF.
- The event with the lowest probability is removed iteratively, increasing the NRE of the distribution, until the null hypothesis of A-D is accepted ($h = 1$).

3.2. Comparison of NREs and PDF selection. The best-fitted PDF is taken as that with the lowest NRE, i.e., that with the largest data population.

4. Fitted PDFs. After analyzing the entire set of groups, the output of the proposed algorithm is composed of the selected PDFs for each one of them.

Once a PDF has been selected for each one of the considered groups, the number of bins and their width for the representation of the results are taken as those with the highest p-value in a $\mathscr{X}^2$ test.



a) Without applying the proposed algorithm b) Applying the algorithm

Fig. 1. Loglogistic PDF fitted for 15/20 kV group.

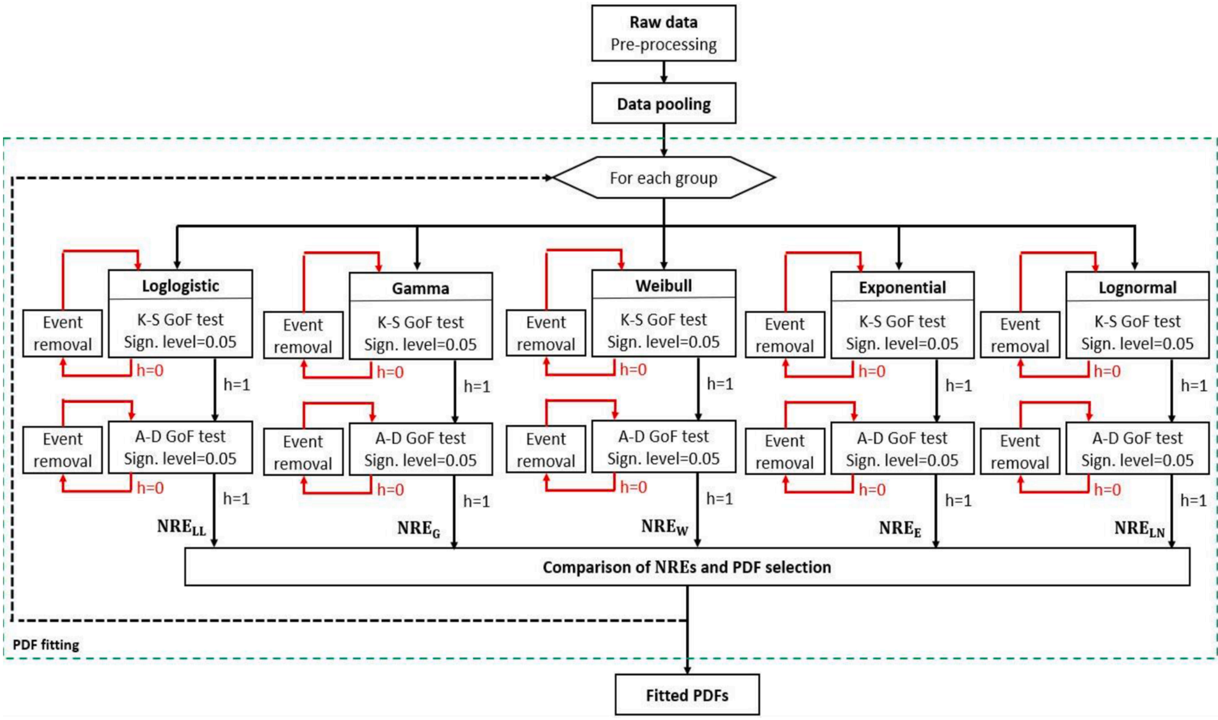


Fig. 2. Flowchart of the proposed algorithm.

4. Results

The performance of the proposed algorithm is assessed in this section. Data from 2001 to 2012 will be considered for the distribution fitting, while the information from 2013 will be used in the next section for validation purposes. Table 1 shows the results obtained for the statistical characterization of SRTs for both aggregated and disaggregated groups. The information included in this table is as follows:

- Number of events in the group before pre-processing.
- Sample mean and standard deviation calculated from raw data.
- Number of events in the group after pre-processing.
- Number of events after applying the proposed method.
- Best-fitted PDF and adjusted distribution parameters with the corresponding mean and standard deviation.
- The 95% and 99% confidence intervals (CI) of the estimated SRTs.

It can be observed that only the groups 15/20 kV and TTI 20 kV required data removal in order to obtain a correctly fitted PDF according to the GoF tests. Respectively, 96 and 51 events were removed from a total of 1782 and 1120. In all cases, the log-logistic distribution resulted to be the most adequate to represent the observed data.

Additionally, substantial differences are observed between the mean and standard deviation calculated from the raw data and those obtained using the fitted PDF. For the aggregated SRT, the mean value obtained from the adjustment was 1.515 h, with a covariance close to two hours. Regarding the disaggregated groups, the highest mean SRT values were obtained for Slice15kV and TTI15kV, with an interruption time over two hours in both cases. Finally, Figs. 3 and 4 represent the observed data for these groups jointly with their adjusted PDFs and the cumulative density functions (CDFs).

5. Validation of results

The adjusted PDFs in the previous section can be used to estimate SRTs in radially-exploited meshed networks. In this section, information

Table 1
Information of the raw data and the fitted PDF for each group.

Service restoration times - Underground cables - Fitted PDFs							
Group	Aggregated 15/20 kV	Disaggregated TTI 15 kV	TTI 20 kV	OPI 15 kV	OPI 20 kV	SLICE 15 kV	SLICE 20 kV
Initial number of samples	1782	440	1120	17	54	27	124
Sample mean (hours)	2.411	2.245	2.544	1.650	2.953	2.305	1.681
Sample standard deviation (hours)	6.641	2.955	8.013	1.091	6.122	2.056	2.098
Number of samples after applying the algorithm	1686	440	1069	17	54	27	124
Best-fitted PDF	**Loglogistic**	**Loglogistic**	**Loglogistic**	**Loglogistic**	**Loglogistic**	**Loglogistic**	**Loglogistic**
μ parameter	0.193	0.330	0.182	0.279	0.251	0.475	0.189
σ parameter	0.360	0.469	0.354	0.290	0.462	0.469	0.396
Mean (hours)	**1.515**	**2.057**	**1.489**	**1.523**	**1.881**	**2.382**	**1.588**
Standard deviation (hours)	1.417	4.973	1.351	0.980	4.123	5.848	1.865
95% CI. Lower limit	0.421	0.350	0.423	0.563	0.329	0.404	0.376
95% CI. Upper limit	3.496	5.526	3.406	3.101	5.018	6.404	3.882
99% CI. Lower limit	0.232	0.162	0.235	0.349	0.154	0.186	0.195
99% CI. Upper limit	6.330	11.980	6.120	5.010	10.765	13.900	7.469

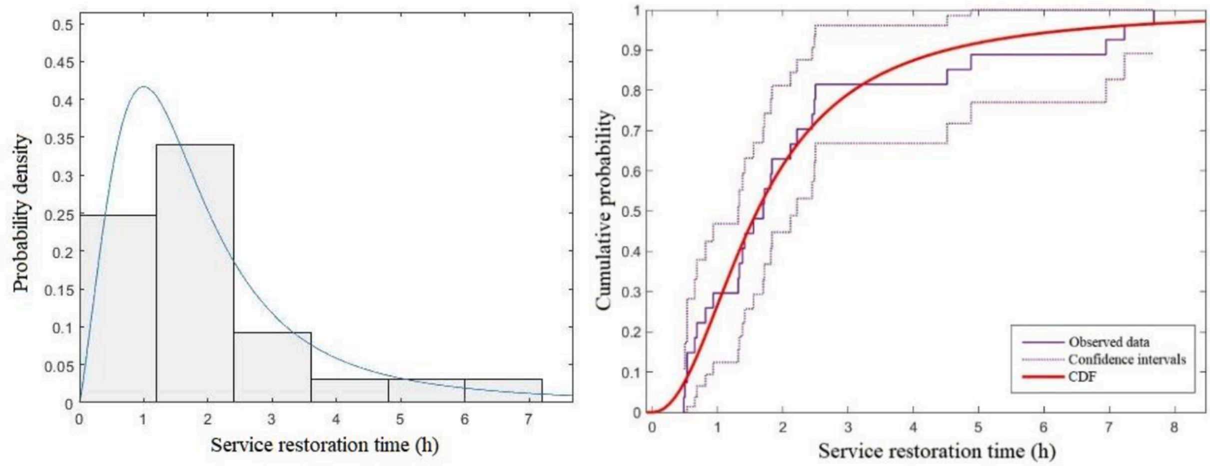


Fig. 3. Histogram of Slice15 kV, PDF (a) and CDF (b).

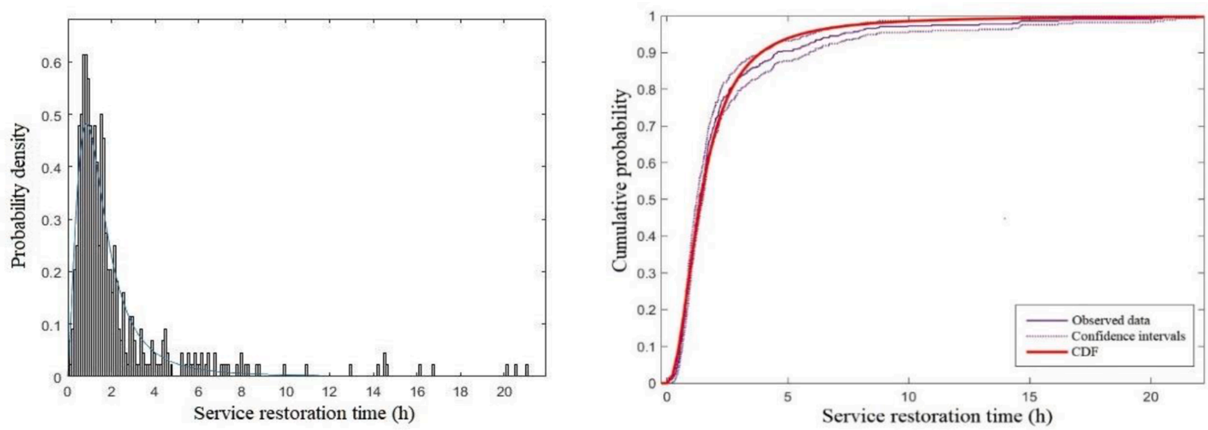


Fig. 4. Histogram of TTI15 kV, PDF (a) and CDF (b).

of system failures from 2013 will be considered to compare observed and estimated restoration times, so that the proposed procedure can be evaluated. The network is composed by 350 MV feeders, with 100 reported failures during 2013. In the sequel, the validation results are shown considering aggregated and desegregated groups. For the aggregated 15/20 kV group, Fig. 5 shows both estimated and observed SRTs, jointly with 95% and 99% CIs. For the sake of clarity, the observed restoration times are represented in descending order. It can be noticed that only thirteen elements (13%) presented SRT values out of the 95% CI, while this number is reduced to seven elements for the 99% CI, which represents 7.00%.

Regarding the validation of the PDFs obtained for the disaggregated groups, the observed SRTs in 2013 have been divided according to these groups of elements. Fig. 6 represents the results obtained for the groups TTI15 kV (Fig. 6a), TTI20 kV (Fig. 6b), Slice15 kV (Fig. 6c), and Slice20 kV (Fig. 6d). No failures were reported for the group OPI15 kV in 2013, while a single value of observed SRT was recorded for the group OPI20 kV. For this reason, these groups are not included in the graphs.

It is observed how the resulting number of cases out of the CIs is lower than those obtained for the aggregated group, concluding that the

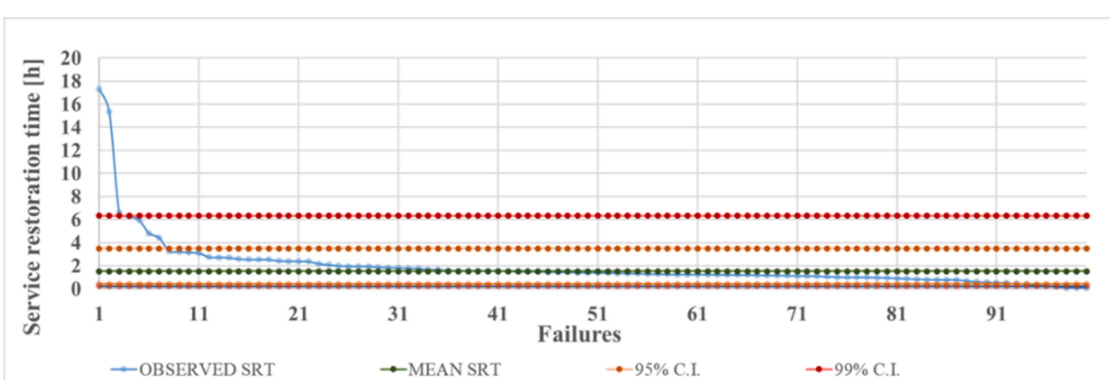


Fig. 5. Estimated and observed SRTs for the aggregated group.

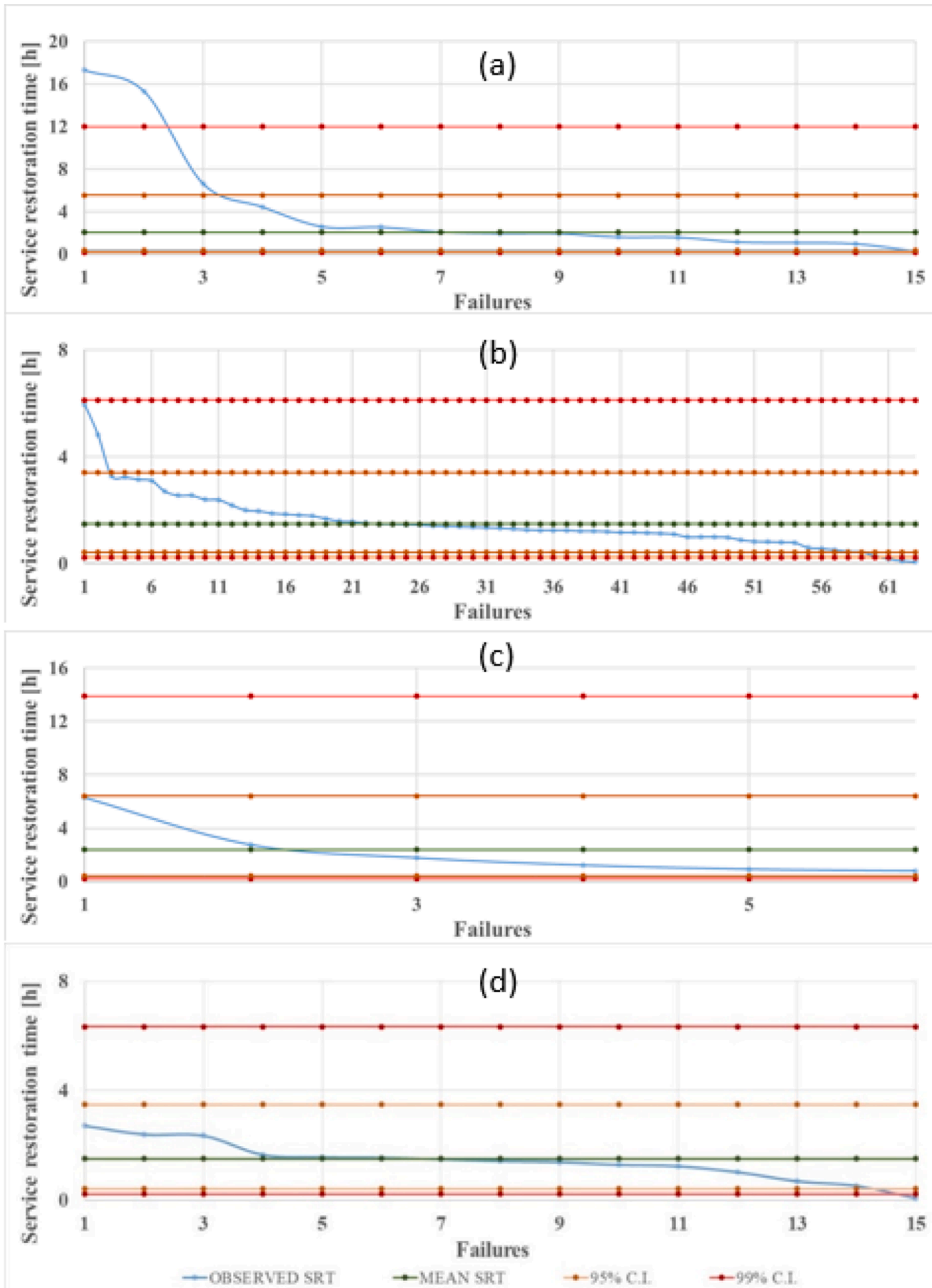


Fig. 6. Estimated and observed SRTs for the disaggregated groups: a) TTI15 kV, b) TTI20 kV, c) Slice15 kV, d) Slice20 kV.

disaggregated estimate of the SRT represents more accurately the real observations, compared to the 15/20 kV group.

6. Discussion

In this section, the results presented previously are summarized and discussed using Tables 2 and 3. First, Table 2 includes the results obtained when a 95% CI is estimated for the SRTs. It can be noticed that, as stated previously, the accuracy is higher for the disaggregated groups, compared to the aggregated 15/20 kV group.

In this table, the number of cases with observed SRTs has been distinguished below the lower limit (LL) of the 95% CI and the situations where the restoration time is above the upper limit (UL). The reason for such a distinction is that, in the first case (SRT<LL), even though the proposed algorithm has provided an inaccurate interval for the SRT, the estimate will be on the conservative side. Taking this matter into account, it can be concluded from Table 2 that, for disaggregated groups, 93% observed SRTs are lower than the UL of the 95% CI. For the disaggregated groups, the most unfavorable case turns out to be the TTI15 kV group, with 80% observed restoration times under the UL. For the 100 failures reported in 2013, the resulting number of SRTs under the UL for the six disaggregated groups is 95, so the results are more accurate in this case, compared to the aggregated 15/20 kV group. However, considering both aggregated and disaggregated groups, the proposed estimation technique provides accurate intervals for restoration times, which can be subsequently used in the calculation of KPIs of the network under consideration, such as SAIDI.

If a more conservative range is desired for the SRT, a 99% CI can be estimated using the presented method, the results being summarized in Table 3. As for the 95% CI, the most accurate results are obtained using

Table 2
Summary of 95% CIs for SRTs.

Group	No of failures	Observed SRTs inside the CI	Observed SRTs outside the CI			
			Total	SRT<LL	SRT>UL	SRT<UL (%)
Aggregated 15/20 kV	100	87	13	6	7	93
TTI15 kV	15	11	4	1	3	80
TTI20 kV	63	57	6	4	2	96.83
OPI15 kV	–	–	–	–	–	–
OPI20 kV	1	1	0	0	0	100
Slice15 kV	6	6	0	0	0	100
Slice20 kV	15	14	1	1	0	100
Sum of disaggregated	100	89	11	6	5	95

Table 3
Summary of 99% CIs for SRTs.

Group	No of failures	Observed SRTs inside the CI	Observed SRTs outside the CI			
			Total	SRT<LL	SRT>UL	SRT<UL (%)
Aggregated 15/20 kV	100	93	7	4	3	97
TTI15 kV	15	13	2	0	2	86.67
TTI20 kV	63	60	3	3	0	100
OPI15 kV	–	–	–	–	–	–
OPI20 kV	1	1	0	0	0	100
Slice15 kV	6	6	0	0	0	100
Slice20 kV	15	14	1	1	0	100
Sum of disaggregated	100	94	6	4	2	98

the disaggregated groups. In this case, 97% observed SRTs were lower than the estimated UL for the aggregated group, while this percentage is 98% if disaggregated groups are considered. These results prove the accuracy of the method for the statistical characterization of SRTs proposed in this paper. Furthermore, it can be concluded that the accuracy of the presented algorithm is higher when disaggregated groups are considered.

The expected SRT values obtained with the proposed method, using aggregated and disaggregated groups, can be used to estimate the SAIDI of the entire network under study, in order to evaluate the reliability of the system. SAIDI reported during 2013 was 58.015 min/customer. If the aggregated 15/20 kV group is considered, the expected SAIDI is 48.861 min/customer, while this value results in 51.748 min/customer when disaggregated groups are analyzed. Finally, if the sample mean from the raw data is used to calculate the SAIDI, the obtained value is 77.753 min/customer. It can be noticed that the proposed algorithm provides more accurate estimations of this indicator, considering both aggregated and disaggregated groups. In a similar analysis carried out using the reported data from 2001 to 2012, the estimations obtained from the fitting PDFs were closer to the reported values in 10 out of these 12 years, giving evidence of the accuracy of the proposed method. Finally, the presented fitting procedure could be used to determine a confidence interval for the SAIDI, which could be used for a risk evaluation of the network. This kind of analysis would not be possible if raw data were used to estimate the SAIDI of the system.

7. Conclusions

This paper presents an algorithm for the statistical characterization of service restoration times, applied to underground cables in MV networks. This procedure sequentially removes low-probability events from the historical record, according to the value of the PDF considered in each case. Two separate GoF tests are used to determine whether the observed data can be represented by the corresponding distribution. The samples are combined into aggregated and disaggregated groups, according to the characteristics and voltage level of the analyzed equipment.

In all cases, the proposed technique selected the loglogistic distribution as the one which best fits the reported data. For the aggregated group, the mean SRT is 1.515 h. Regarding the six disaggregated groups considered in this work, Slice15 kV and TTI15 kV presented the highest expected SRTs, both over two hours. The lowest restoration time was obtained for TTI20 kV, with an expected SRT below 1.5 h.

The fitted PDFs have been assessed in their ability to predict the mean values of SRTs in a real MV network, also providing a confidence interval for these restoration times. For a whole year of information, SRTs have been calculated for a total of 100 faulty elements. The results presented show the accuracy of the proposed method, especially when disaggregated groups are considered. Taking a 95% CI, the observed SRT was lower than the upper limit of the interval in 95% of the cases. This percentage increases to 98% of cases if a 99% CI is used as a more conservative approach. When the expected SRT values obtained with the proposed method are used to estimate the KPIs of the whole network, disaggregated groups present more accurate results, with a SAIDI equal to 51.748 min/customer, the reported value being 58.015 min/customer.

The probability functions provided by the proposed algorithm can be used by the operators of distribution networks to build system reliability models, such as those based on Monte Carlo simulations. The reliability of the electrical network can be accurately estimated by means of these models, according to the corresponding topology. In this context, future work can be oriented to the application of the proposed method to different elements of the system and voltage levels, and using the fitted PDFs in Monte Carlo simulations, so that confidence intervals for system KPIs can be obtained.

CRediT authorship contribution statement

J.A. Clavijo-Blanco: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. **M.A. González Cagigal:** Conceptualization, Methodology, Data curation, Writing – original draft, Writing – review & editing. **J.A. Rosendo-Macías:** Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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