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Statistical Characterization of Reliability Parameters in Medium-Voltage Networks: A Comprehensive Analysis

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Abstract. In the context of reliability of distribution networks, this work provides a statistical characterization of key reliability parameters for effective management of medium-voltage (MV) networks. Specifically, six parameters are analyzed, namely time to locate, time to switch, time to start repair, time to repair, time to restore normal configuration, and time between failures. A statistical fitting procedure is applied to data obtained from a distribution system operator (DSO) database. This work considers both aggregated and disaggregated groups of MV network components. The obtained results show that overhead lines exhibit the longest location times, whereas underground cables takes the longest repair durations. The presented statistical characterization provides useful data for developing elaborated reliability models of MV networks with similar configurations and might be used as a valuable benchmark for future studies.
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Keywords. Distribution Network Operation, Failure Management, Reliability Parameters, Statistical Characterization

1. Introduction

Despite the great importance of reliability in electric power systems for an adequate operation, relatively few studies focus on characterizing this specific property. This research gap may stem from multiple factors, such as data unavailability or the lack of a comprehensive reliability definition, as noted in [1]. Furthermore, given that the transmission network is regarded as the backbone of the electrical system, medium-voltage distribution networks have been comparatively less prioritized in this context. Nevertheless, the critical importance of distribution networks should not be underestimated, as they play a key role due to their direct connection with different customers, [2], where distributed generation and the connection of new loads, such as electric vehicles, are rapidly growing.

In this regard, DSOs are compelled to ensure adequate service quality for their clients, [3]. As part of these obligations, DSOs must document network incidents and store this information in databases. These recordings are crucial for accurately estimating reliability parameters.

From a technical perspective, service quality in electric power systems is defined by three fundamental concepts: continuity of supply, product quality, and customer service, [4]. Within this framework, reliability (included in the first concept) is directly characterized by the frequency and duration of supply interruptions, [5]. These two parameters allow for the calculation of some key performance indicators (KPIs), such as system average interruption frequency index (SAIFI) and system average interruption duration index (SAIDI), which might be used as a mean to quantify the overall reliability of the system, [6]. In some countries, these KPIs are even used to impose financial penalties on DSOs if they fail to meet established standards, [5]. Furthermore, reference [4] lists a set of reliability parameters that could be useful to quantify these KPIs, if the required information is available.

Moreover, reference [7] introduces the so-called granular reliability parameters by subdividing the total service restoration time into distinct intervals. By optimizing these intervals, such as fault location time (duration between receiving notification of incident and the fault being located) and switching time (the duration between fault detection and network reconfiguration, [8]), overall restoration time can be significantly reduced, as remarked in [7] and in [9]. By minimizing interruption intervals, DSOs can improve key performance indicators (KPIs) like SAIFI and SAIDI, which quantify system reliability [5, 6]. In this regard, [7] and [10] underscore the potential for enhanced customer satisfaction through reduction of these intervals, while [11] presents a multi-objective algorithm specifically designed to minimize switching time during the restoration process.

It has been highlighted the need for DSOs to monitor, estimate, and optimize reliability parameters to ensure regulatory compliance. Additionally, the growing integration of renewable energy sources and energy storage devices as distributed generation is driving the need for a comprehensive analysis of the reliability performance of distribution power networks [12]. To achieve this, reliability models are employed for the corresponding distribution systems. Effectively integrating reliability parameters in these models requires a proper statistical characterization using probability density functions (PDFs), which provide a more comprehensive representation of data, compared to average values alone, [4].

To address this issue, this paper implements a statistical fitting procedure to characterize several reliability parameters for various components in MV networks, considering aggregated and disaggregated groups of elements from a DSO database. The main contribution of this work is the detailed statistical characterization of these parameters, enabling their use in developing accurate reliability models for distribution grids.

2. Description of the fitting procedure

The considered procedure aims to fit real-world data extracted from DSO databases to an appropriate PDF for use in reliability models of distribution networks. This technique has been already presented by the authors in [13], where it was specifically applied to characterize service restoration times for underground MV cables. Through this process, expected values and confidence intervals were derived, which cannot be directly obtained from raw data.

The algorithm iteratively identifies and removes low-probability events, by evaluating five different PDFs. The most appropriate of these distributions is selected according to two goodness of fit (GoF) tests. A brief overview of this procedure is provided below.

2.1. Pre-processing

The initial step involves removing data inconsistencies, such as negative or unrealistic values that may arise from recording errors.

2.2. Data Pooling

Two approaches are considered for processing the raw data from the different components of the network. The first one treats the entire data population for each component as an aggregated group. The second approach considers disaggregated groups, classifying components based on voltage level or insulation types (e.g., thermoplastic, thermosetting, oil paper).

In this paper, the following aggregated groups are considered: underground cables (UC 15/20 kV), overhead lines (OL 15/20 kV), substation common electrical devices (SCED 15/20 kV), MV/LV transformers (T 15/20 kV), load-break switches (LBS 15/20 kV), isolating switches (IS 15/20 kV) and fuse load-break switches (FLBS 15/20 kV). Meanwhile, the disaggregated groups are: thermoplastic and thermosetting insulated cables for 15 kV (TTI15 kV) and 20 kV (TTI20 kV), oil-paper insulation for 15 kV (OPI15 kV) and 20 kV (OPI20 kV), substation common electrical devices in 15 kV (SCED 15 kV) and 20 kV (SCED 20 kV), MT/LV transformers in 15 kV (T 15 kV) and 20 kV (T 20 kV), load-break switches in 15 kV (LBS 15 kV) and 20 kV (LBS 20 kV), isolating switches in 15 kV (IS 15 kV) and 20 kV (IS 20 kV), and fuse load-break switches in 15 kV (FLBS 15 kV) and 20 kV (FLBS 20 kV).

More information about data pooling and the considered groups can be found in [14].

2.3. PDF fitting

To determine the best statistical characterization, each data group is fitted to five different distributions: exponential, gamma, Weibull, lognormal, and loglogistic. These PDFs are defined in Table I. The parameters of each distribution are included in the table as Parameter 1 (P-1) and Parameter 2 (P-2).

Table I. – PDF definitions

PDF	Function	P-1	P-2
Exponential	$f(x) = \frac{1}{\mu} e^{\frac{-x}{\mu}}$	μ (mean)	-
Gamma	$f(x) = \frac{1}{b^a \Gamma(a)} x^{a-1} e^{\frac{-x}{b}}$	a (shape)	b (scale)
Weibull	$f(x) = \frac{\beta x^{\beta-1}}{\alpha^\beta} e^{\left[-\left(\frac{x}{\alpha}\right)^\beta\right]}$	α (scale)	β (shape)
Lognormal	$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\left[-\frac{(\ln x-\mu)^2}{2\sigma^2}\right]}$	μ (mean of logarithmic values)	σ (standard deviation of logarithmic values)
Loglogistic	$f(x) = \frac{1}{\sigma x} \frac{e^z}{[1+e^z]^2}$ $z = \frac{\log(x) - \mu}{\sigma}$	μ (mean of logarithmic values)	σ (scale parameter of logarithmic values)

After fitting these PDFs, two GoF tests are employed to evaluate each function. First, the Kolmogorov-Smirnov (K-S) test is applied, followed by the Anderson-Darling (A-D) test, both performed considering a significance level equal to 0.05. For each GoF test, if the null hypothesis (no difference between the observed and the theoretical distribution) is rejected, the event with the lowest probability, according to the fitted PDF, is identified and removed. This iterative process continues until the null hypothesis is accepted for both GoF tests.

Among the considered PDFs, the one with the smallest number of removed events is taken as the best fitted for the corresponding group. This approach ensures that the chosen PDF minimizes the exclusion of observed events.

3. Case study

In this paper, incident data from 2001-2013 in a weakly-meshed, radially-operated Spanish MV were extracted from a DSO database, [14]. Following Spanish regulatory standards and in accordance with European technical standards EN50160 (see [5]), faults lasting less than 3 minutes were excluded, focusing the analysis on permanent interruptions.

For this network, the fitting procedure has been described and validated for the specific case of service restoration times in [13] and [15]. In this case, the same procedure is applied to all available times in the database for the aggregated and disaggregated groups of elements.

The fault database of the DSO provides information on the timestamps in different states of an incident. These are listed and defined below:

- Start time (ST): moment when the fault is registered in the system.
- Location time (LT): moment when the fault is located.
- Restore time (RT): when the network topology allows for isolating the fault and the electrical supply is restored through an alternative path.
- Start time of repair (STR): once the affected element has been located and isolated from the network, repair or replacement work can begin.
- End time of repair (ERT): when the affected element has been repaired.

From these timestamps, the following reliability parameters can be defined:

- Time to locate (TTL): time elapsed between the receiving notification of incident and the fault being located. Calculated for each recorded fault as:

$$TTL = LT - ST$$

- Time to switch (TTS): time to fault location and isolation through network reconfiguration, enabling supply to unaffected customers. Calculated as:

$$TTS = ETF - LT$$

- Time to start repair (TTSR): this time involves the period from fault location to the start of repair:

$$TTSR = STR - LT$$

- Time to repair (TTR): duration of the repair process (component repair or replacement). Calculated as:

$$TTR = ERT - STR$$

- Time to return to normal configuration (TTRNC): total time involved in a fault, calculated as:

$$TTRNC = ERT - ST$$

- Time between failures (TBF): time elapsed between consecutive network faults, i and i+1. Calculated as:

$$TBF = ST\,(i+1) - ST\,(i)$$

For a clearer understanding of these concepts, Figure 1 shows the different states of the network whose timestamps are available in the database, together with the corresponding reliability parameters described previously.

4. Results and discussion

This section presents the results of applying the fitting method to the various reliability parameters and element groupings previously presented. Each case is summarized in a table detailing the best fitted PDF, its statistical parameters, P-1 and P-2, and the corresponding mean value. When no PDF satisfied both K-S and A-D tests, a fit satisfying at least one of these GoF test was accepted and is marked in red in the corresponding tables.

Table II presents the results for the TTL. Based on the mean values, the components with the longest times are the OL and the FLBS 15kV, with 2.43 and 2.27 h, respectively.

Table II. – Statistical information for TTL [h]

		Mean	PDF	P-1	P- 2
UC	15/20 kV	1.0699	Weibull	1.2081	2.1631
	TTI 15 kV	1.2241	Loglogistic	-0.0367	0.3719
	TTI 20 kV	1.3237	Loglogistic	0.0719	0.3486
	OPI 15 kV	1.3120	Lognormal	0.1879	0.4091
	OPI 20 kV	1.5834	Loglogistic	0.1768	0.4028
OL	15/20 kV	2.4260	Exponential	2.4260	-
SCED	15/20 kV	1.3637	Exponential	1.3637	-
	15 kV	1.3513	Weibull	1.1170	0.7359
	20 kV	1.3764	Gamma	2.7747	0.4961
T	15/20 kV	1.8534	Gamma	5.0432	0.3675
	15 kV	2.0908	Gamma	6.4487	0.3242
	20 kV	1.6110	Exponential	1.6110	-
LBS	15/20 kV	1.5531	Gamma	0.5565	2.7909
	15 kV	1.2894	Gamma	0.5343	2.4133
	20 kV	1.7332	Exponential	1.7332	-
IS	15/20 kV	1.3269	Gamma	0.4150	3.1972
	15 kV	1.2838	Gamma	0.3966	3.2367
	20 kV	1.8222	Exponential	1.8222	-
FLBS	15/20 kV	1.6078	Gamma	0.4004	4.0153
	15 kV	2.2750	Exponential	2.2750	-
	20 kV	1.3202	Gamma	0.3679	3.5887

Table III presents the fitting results for TTS, indicating transformers as taking the longest time to switch (4.56 h). The 20 kV MV/LV transformer group exhibits a notably lower TTS value (1.29 h) due to the removal of 36 outliers during the fitting process, the original sample mean being 5.99 h. As the removal of so many outliers has a major effect on the results, rejecting this fit might be considered.

Table III. – Statistical information for TTS [h]

		Mean	PDF	P-1	P-2
UC	15/20 kV	1.4586	Lognormal	-2.1384	2.2432
	TTI 15 kV	1.6672	Lognormal	-1.8153	2.1571
	TTI 20 kV	1.3600	Lognormal	-2.3011	2.2860
	OPI 15 kV	0.3400	Lognormal	-2.6946	1.7992
	OPI 20 kV	2.5153	Lognormal	-2.3837	2.5714
OL	15/20 kV	2.0289	Gamma	0.6518	3.1126
SCED	15/20 kV	2.5960	Gamma	0.5510	4.7113
	15 kV	3.7730	Gamma	0.3928	9.6042
	20 kV	1.9067	Exponential	1.9067	-
T	15/20 kV	4.5623	Weibull	3.6255	0.7044
	15 kV	4.0634	Exponential	4.0634	-
	20 kV	1.2957	Exponential	1.2957	-
LBS	15/20 kV	3.5482	Weibull	2.6911	0.6719
	15 kV	3.5968	Weibull	2.8487	0.7019
	20 kV	2.2111	Exponential	2.2111	-
IS	15/20 kV	3.0865	Weibull	2.5449	0.7338
	15 kV	3.1659	Weibull	2.5579	0.7171
	20 kV	2.3548	Exponential	2.3548	-

FLBS	15/20 kV	2.7281	Weibull	2.3495	0.7740
	15 kV	1.7383	Exponential	1.7383	-
	20 kV	3.2933	Exponential	3.2933	-

Table IV presents the results for TTSR. While IS 20 kV requires the longest time (13.53 h), this result is based on only seven failures throughout the study period. Excluding this result, the remaining groups show times ranging from 1 to 6 h. Within the aggregated groups, FLBS and UC exhibit the longest times (5.15 and 4.93 h, respectively).

Table IV. – Statistical information for TTSR [h]

		Mean	PDF	P-1	P-2
UC	15/20 kV	4.9329	Weibull	2.2960	0.4816
	TTI 15 kV	6.0321	Weibull	2.7699	0.4783
	TTI 20 kV	4.8847	Weibull	2.2225	0.4762
	OPI 15 kV	6.3188	Lognormal	0.3956	1.7017
	OPI 20 kV	2.7618	Gamma	0.4055	6.8117
OL	15/20 kV	2.8913	Exponential	2.8913	-
SCED	15/20 kV	4.1258	Weibull	1.1371	0.3878
	15 kV	1.3510	Gamma	0.3257	4.1487
	20 kV	2.9350	Weibull	1.2770	0.4659
T	15/20 kV	2.8127	Weibull	1.3294	0.4854
	15 kV	2.7568	Gamma	0.3295	8.3661
	20 kV	2.7679	Weibull	1.4367	0.5104
LBS	15/20 kV	3.0143	Gamma	0.3610	8.3504
	15 kV	2.7684	Weibull	1.0671	0.4411
	20 kV	2.6045	Gamma	0.4406	5.9112
IS	15/20 kV	1.8489	Gamma	0.3268	5.6576
	15 kV	2.6855	Gamma	0.2892	9.2847
	20 kV	13.5333	Gamma	0.3344	40.4713
FLBS	15/20 kV	5.1558	Weibull	1.9028	0.4330
	15 kV	6.3196	Weibull	2.9636	0.4834
	20 kV	3.9833	Gamma	0.3453	11.5360

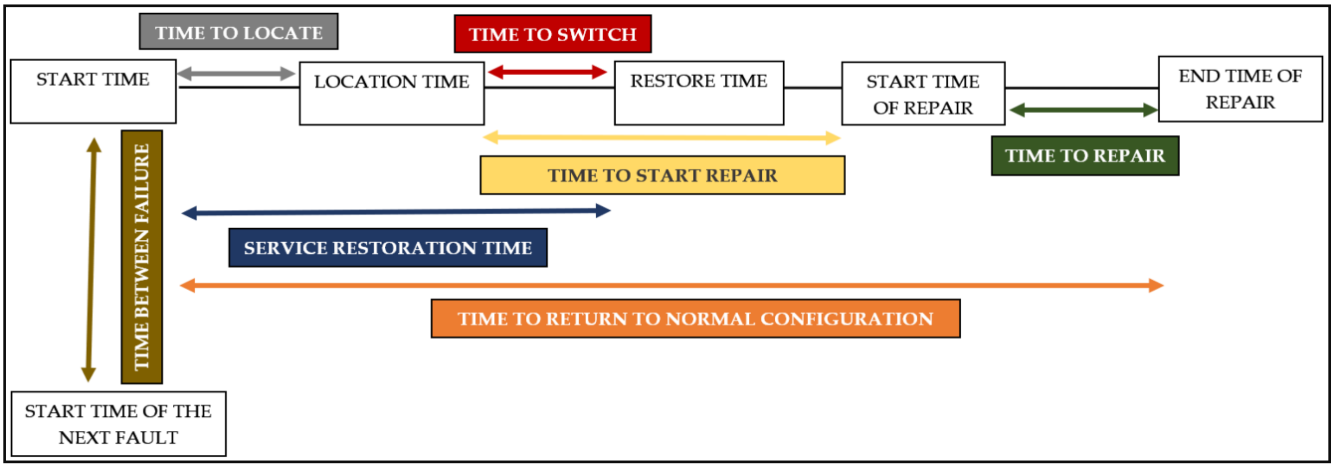

Fig. 1. Timestamps and reliability parameters according to the information contained in DSO database

The results of applying the fitting procedure to TTR are presented in Table V. In this case, the disaggregated groups of elements with the highest TTR are TTI 15 kV and OPI 20 kV, with 15.20 and 14.25 h, respectively, both within the aggregated UC group.

Table V. – Statistical information for TTR [h]

		Mean	PDF	P-1	P-2
UC	15/20 kV	9.7769	Exponential	9.7769	-
	TTI 15 kV	15.2022	Loglogistic	1.7835	0.6828
	TTI 20 kV	9.7357	Gamma	11.0546	0.8807
	OPI 15 kV	11.1837	Weibull	12.6077	1.9216
	OPI 20 kV	14.2559	Gamma	10.2853	1.3860
OL	15/20 kV	7.9464	Loglogistic	0.7369	0.7779
SCED	15/20 kV	6.3162	Loglogistic	0.6179	0.7548
	15 kV	3.7058	Weibull	3.2617	0.7969
	20 kV	3.0307	Exponential	3.0307	-
T	15/20 kV	4.3116	Weibull	4.4459	1.0836
	15 kV	10.3730	Loglogistic	1.2757	0.7166
	20 kV	4.6597	Lognormal	0.9766	1.0605
LBS	15/20 kV	6.8505	Gamma	0.5270	12.9980
	15 kV	3.7199	Gamma	0.6521	5.7049
	20 kV	8.8372	Gamma	0.5152	17.1521
IS	15/20 kV	5.1224	Loglogistic	0.8781	0.6256
	15 kV	5.4020	Loglogistic	0.8874	0.6403
	20 kV	3.4892	Lognormal	0.8374	0.9081
FLBS	15/20 kV	4.8890	Weibull	3.5122	0.6394
	15 kV	7.0852	Exponential	7.0852	-
	20 kV	3.9608	Exponential	3.9608	-

Table VI presents the results for TTRNC. Underground cables exhibit the longest times, particularly the disaggregated groups TTI 20 kV and TTI 15 kV, with 22.72 and 20.39 h, respectively.

Table VI. – Statistical information for TTRNC [h]

		Mean	PDF	P-1	P-2
UC	15/20 kV	21.8095	Loglogistic	2.2767	0.6424
	TTI 15 kV	20.3915	Loglogistic	2.2955	0.6130
	TTI 20 kV	22.7284	Loglogistic	2.2413	0.6664
	OPI 15 kV	15.7726	Weibull	17.8082	2.1006
	OPI 20 kV	17.6690	Weibull	19.3362	1.3778
OL	15/20 kV	8.1308	Loglogistic	1.5631	0.5383
SCED	15/20 kV	6.9914	Loglogistic	1.2045	0.6202
	15 kV	5.0411	Gamma	0.9062	5.5631
	20 kV	6.1005	Loglogistic	1.2454	0.5516
T	15/20 kV	8.3222	Loglogistic	1.6295	0.5184
	15 kV	11.1130	Loglogistic	1.7466	0.5915
	20 kV	6.4234	Loglogistic	1.5300	0.4330
LBS	15/20 kV	9.8008	Lognormal	1.4339	1.3027
	15 kV	7.5346	Lognormal	1.3035	1.1966
	20 kV	11.2103	Gamma	0.6732	16.6522
IS	15/20 kV	7.7314	Lognormal	1.4082	1.1288
	15 kV	6.9969	Loglogistic	1.2819	0.5923
	20 kV	16.8738	Gamma	0.6590	25.6058
FLBS	15/20 kV	11.8220	Lognormal	1.2576	1.5571
	15 kV	7.8801	Lognormal	1.4888	1.0729
	20 kV	7.9383	Gamma	0.6560	12.1005

Since TTRNC is an important reliability parameter, a comparison is presented in Table VII between the obtained values and those published in [4], [16] and [2]. The average value for each group is included in the table. Due to lack of published data, some groups could not be compared.

In light of this table, it is noticeable that the mean values obtained for each grouping with the fitting procedure are significantly higher than those published in [4], which were derived from values found in several sources, such as historical data from distributors, manufacturer test data, IEEE and CIGRE reports, etc. However, when comparing the results with those from [16] and [2], it can be seen that the mean values obtained for each group in the fitting procedure are substantially lower.

Table VII. – Benchmarking of TTRNC [h]

		TTRNC	*Benchmarking*		
		Fitting method	[4]	[16]	[2]
UC	15/20 kV	21.8	10.0	56.2	48.0
	TTI 15 kV	20.4	-	-	-
	TTI 20 kV	22.7	-	-	-
	OPI 15 kV	15.8	-	-	-
	OPI 20 kV	17.7	-	-	-
OL	15/20 kV	8.1	4.0	9.5	-
SCED	15/20 kV	7.0	-	-	-
	15 kV	5.0	-	-	-
	20 kV	6.1	-	-	-
T	15/20 kV	8.3	6.5	70	120
	15 kV	11.1	-	-	-
	20 kV	6.4	-	-	-
LBS	15/20 kV	9.8	2.5	120.9	48
	15 kV	7.5	-	-	-
	20 kV	11.2	-	-	-
IS	15/20 kV	7.7	4.0	120.9	48
	15 kV	7.0	-	-	-
	20 kV	16.9	-	-	-
FLBS	15/20 kV	11.8	2.5	120.9	48
	15 kV	7.9	-	-	-
	20 kV	7.9	-	-	-

These differences likely arise from variations in data sources and locations. The present study utilizes data from a single distributor, reflecting their specific operational procedures and fault response. This underscores the importance of network-specific reliability parameters and the value of statistical analysis methods such as the one proposed in [15] and applied here. However, for DSOs lacking detailed fault records, the statistically characterized parameters presented here can be used as a reference for similarly configured networks.

Finally, Table VIII presents the results for TBF. While IS 20 kV shows the longest time (12985 h), this is attributable to the low number of recorded incidents. Among aggregated groups, underground cables, overhead lines, and transformers exhibit the shortest times between failures (59, 401, and 531 h, respectively).

Table VIII. – Statistical information for TBF [h]

		Mean	PDF	P-1	P-2
UC	15/20 kV	59.6	Gamma	0.7	80.3
	TTI 15 kV	236.3	Weibull	209.7	0.8
	TTI 20 kV	94.8	Gamma	0.7	132.0
	OPI 15 kV	6491.9	Gamma	0.5	13555.1
	OPI 20 kV	2302.6	Lognormal	6.3	1.7
OL	15/20 kV	401.2	Weibull	332.2	0.7
SCED	15/20 kV	872.2	Gamma	0.6	1545.5
	15 kV	3148.0	Lognormal	7.0	1.5
	20 kV	1377.1	Gamma	0.5	2988.8
T	15/20 kV	531.6	Weibull	412.4	0.7
	15 kV	1048.8	Weibull	862.6	0.7
	20 kV	1096.6	Gamma	0.7	1660.7
LBS	15/20 kV	1206.5	Weibull	1065.8	0.8
	15 kV	2889.4	Gamma	0.7	4028.5
	20 kV	1699.2	Gamma	0.7	2379.9
IS	15/20 kV	1339.3	Gamma	0.8	1770.8
	15 kV	1471.3	Exponential	1471.3	-
	20 kV	12985.7	Exponential	12985.7	-
FLBS	15/20 kV	1908.8	Exponential	1908.8	-
	15 kV	4959.6	Weibull	5220.6	1.2
	20 kV	2863.2	Exponential	2863.2	-

The TBF values shown in Table VIII have been obtained for the entire network, representing a group of elements for each component. These values could be used to estimate the expected TBF for each individual component within the group, which would be highly useful for application in similar networks with a different number of elements. In this regard, Table IX presents the expected TBF per component, $\boldsymbol{TBF_{pc}}$, calculated using the following expression:

$$\boldsymbol{TBF_{pc} = TBF_i \cdot c}$$

where $\boldsymbol{TBF_i}$ represents the value shown in Table VII for the corresponding group $\boldsymbol{i}$, while c is the number of components in the network under consideration, or the total length in the case of UC or OL.

Table IX. – TBF per component in the network under study

		$\boldsymbol{TBF_{pc}}$	Unit
UC	15/20 kV	66690.478	h·km
	TTI 15 kV	87607.227	h·km
	TTI 20 kV	58502.910	h·km
	OPI 15 kV	85865.767	h·km
	OPI 20 kV	85403.156	h·km
OL	15/20 kV	172743.379	h·km
SCED	15/20 kV	2954946.311	h·component
	15 kV	5062185.489	h·component
	20 kV	2451170.472	h·component
T	15/20 kV	2248228.849	h·component
	15 kV	2105056.333	h·component
	20 kV	2436222.050	h·component
LBS	15/20 kV	7659659.155	h·component
	15 kV	7340162.668	h·component
	20 kV	6471298.680	h·component
IS	15/20 kV	1123087.917	h·component
	15 kV	1183121.635	h·component
	20 kV	447409.983	h·component
FLBS	15/20 kV	5495299.249	h·component
	15 kV	5529332.314	h·component
	20 kV	5050840.795	h·component

5. Conclusion

This paper presents the application of a fitting procedure to statistically characterize various reliability parameters of MV network components, based on data from a DSO database. A total of six reliability parameters have been statistically characterized across six aggregated and fourteen disaggregated groups of components.

Specifically for the aggregated groups, overhead lines presented the longest location time. The MV/LV transformer exhibited the highest time to switch, while the fuse load-break switch had the longest time to start repair. Underground cables showed both the longest time to repair and time to return to normal configuration. Finally, the component with the highest time between failures, making it the least likely to fail in the network, was the fuse load-break switch.

For the disaggregated groups, the component exhibiting the longest location time was the overhead lines. The MV/LV transformer at 15 kV had the highest switching time, whereas the isolating switch at 20 kV required the longest time to start repairs. The underground cables of TTI at 15 kV presented the most prolonged repair duration, while the highest time to return to normal configuration was observed in the underground cables of TTI at 20 kV. Finally, the component with the longest time between failures, thus the least prone to failure within the network, was the isolating switch at 20 kV.

The statistical characterization of these reliability parameters provides a significant contribution to the field of MV network reliability modeling. These results offer valuable input data for developing and refining sophisticated reliability models, particularly for networks with comparable configurations to the one analyzed. Furthermore, the detailed statistical distributions presented here serve as a benchmark for future reliability studies, enabling comparative analyses. This work might contribute to enhanced operational strategies, optimized maintenance planning, and more effective investment decisions to improve grid resilience and customer service.

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