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Federal Department of the Environment, Transport, Energy and Communications DETEC

Swiss Federal Office of Energy SFOE
Energy Research and Cleantech Division

REEL Demo – Romande Energie ELectric network in local balance Demonstrator

Deliverable: 4a1 Study of targeted feeders' operational limits

Demo site: Aigle

Developed by

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in collaboration with Romande Energie

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1. Description of deliverable and goal

1.1. Executive summary

The goal of this deliverable is to study the operational limits of the electrical distribution feeder of Onnens (medium voltage) and Rolle (low voltage) that were initially expected to be used as demonstration sites. Both networks belong to the assets of Romande Energie and are located in the south-west part of Switzerland in the Vaud canton.

We first collect and analyze the load and distributed generation[1] time series in both networks. This task is accomplished by integrating coarse data provided by Romande Energie (RE) with refined data available from the photovoltaic installations of the EPFL-DESL. Concerning the methodology, the operational limits of both networks are assessed using a Probabilistic Load Flow developed at the DESL and based on standard methods existing in the literature.
As described in the report, the Onnens grid may face nodal over-voltage and lines congestions due to the massive injections coming from a single multi-MW PV plant located at the end of the Onnens medium voltage feeder.
On the other hand, the low voltage grids in Rolle are robust against the planned PV installations, i.e., the grids will not suffer any security constraint violations.
In what follows, we first briefly describe the methodology adopted to carry-out the study and then the analysis of the steady-state behavior of both grids.

1.2. Description

The standard Probabilistic Load Flow process

The probabilistic load flow (PLF) is a well-known technique typically applied for short or long-term planning of power systems as well as for steady-state analysis of a grid (e.g., [1, 2, 3]). Contrary to the traditional load flow analysis, where the power flow equations are solved at a specific time instant for fixed power values of loads/ injections, the PLF accounts for the stochasticity associated with loads/injections by considering that these quantities are represented by probability density functions (PDFs) at a given time

[1] In both networks, the distributed generation is solely represented by photovoltaic (PV) power plants.

interval. This allows for a probabilistic assessment of the associated stochastic network state.

The statistical distributions of the network states can be obtained either by using a numerical approach (e.g., [4, 5, 6]) or an analytical method (e.g. [7, 8]). The numerical approach is typically based on Monte Carlo simulations, where a large number of values of loads and injections are sampled from the corresponding distributions and a deterministic load flow is solved for each combination of these values[2]. The analytical approach uses the mathematical expressions of the PDFs of loads/injections and tries to analytically express the statistical distributions of network states usually by approximating the non-linear power flow equations. In this work, we have adopted the former approach. Even though such a method is computationally demanding, it has the benefit that the exact non-linear power flow equations can be used which results in better accuracy of the obtained PDFs of the network states.

The first step towards performing a PLF analysis is to infer the statistical distributions of the loads and injections in the network, namely define their probability density functions for the different periods of the day/month/season/year. With particular reference to the case of active distribution networks, the PV profiles have variations across the seasons and they have dissimilar characteristics for the cloudy and clear sky days. The loads have seasonal variations in addition to dissimilarities in weekdays and weekends. Additionally, their profiles may have variations with respect to the external parameters like temperature and holidays. In this study, we have considered all these variations in order to generate specific scenarios.

The historical data of the parameters (load active/reactive power consumptions and solar irradiation) are collected from RE and empirical measurement at the EPFL-DESL.

In order to statistically characterize the network nodal injections from loads and PV, we assume that the aggregate load or PV plant at the k^{th} time interval of the day denoted hereafter by L_k is a random variable. The time aggregation horizon to perform the PLF is of 15 minutes. Therefore, we have 96 daily intervals and for each time interval, we observe the available samples after removing the outliers and the mean $(L_k - \bar{L}_k)$. An example of the the QQ-plot of the zero-mean data for a specific time interval for a load in Onnens is shown in Fig. 1. The data for the other 95 time intervals are not shown here

[2] Note that, in general, the MC approach allows for taking into account any type of stochastic distribution of load and generation.

for the sake of brevity as they exhibit similar characteristics. As it can be observed, after having removed the outliers, the data exhibit, approximately, a Gaussian distribution.

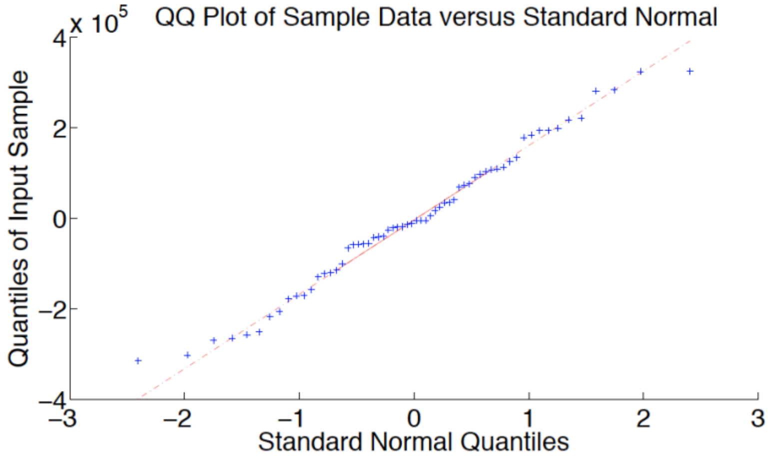


Figure 1 – QQ-plots of zero-mean data for a load in the network of Onnens. Data obtained for a specific time interval (15 minutes) of the day during the winter period. The dataset to infer this kind of plots is of 91 days.

The majority of the approaches adopted so far in the literature to perform PLF studies assumes that the random variables that describe the network nodal injections at different time intervals are independent (e.g., [4, 9]). In this work, we take into account temporal correlation of the random vectors $L_k, k = 1, \ldots, 96$. In this respect, we assume that the random vector $(\mathbf{L} - \bar{\mathbf{L}}) = (L_1 - \bar{L}_1, \ldots, L_{96} - \bar{L}_{96})$ follows a multivariate Gaussian distribution $(\mathbf{L} - \bar{\mathbf{L}}) = \mathcal{N}(0, \Omega)$ where Ω is the covariance matrix that contains the whole information about the variance and covariance of the random variables $(L_k - \bar{L}_k, k = 1, \ldots, 96)$[3].

The sample covariance matrix that will be used to generate a sample of the random vector is obtained empirically using the available zero-mean data in each time interval. The obtained distributions are used to generate scenarios using multivariate normal random numbers for each temporal bin. Once the scenarios for load and PV are generated, they are used to generate the final scenario tree using the technique described in [9] and [10].

[3] 3Note that the rank of the covariance matrix Ω corresponds to the number of considered time steps (i.e., 96). Also note that Ω is a full matrix.

Implementation of the PLF process

The algorithm adopted to implement the PLF is depicted in Figure 2. As above-mentioned, the time resolution of the study is 15 minutes. First, the load and PV profiles are sampled by the process explained in the previous section. Then, for each sample of the stochastic parameters, we solve a load flow problem of the targeted network to obtain the network state from which we derive the nodal voltage magnitudes and lines' current. We continue this process to cover all the plausible scenarios.

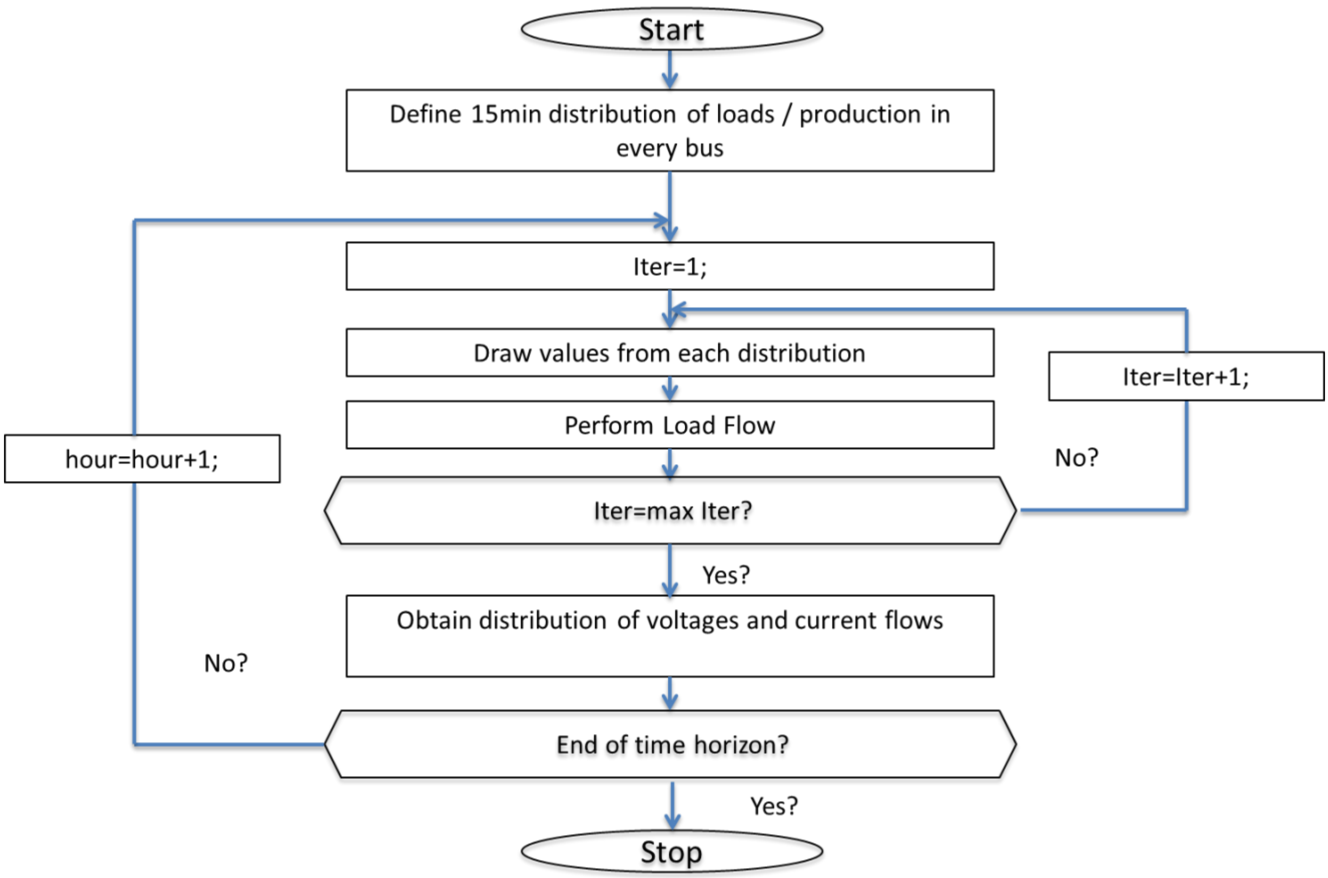


Figure 2 – Implementation of the PLF process.

2. Achievement of deliverable:

2.1. Date

This deliverable has been achieved on December 2017.

2.2. Demonstration of the deliverable

Study of the Onnens medium voltage feeder using the PLF process

The topology of the Onnens medium voltage feeder (20 kV) is shown in Figure 3. The yearly aggregated load consumption and PV production are shown in Figure 4a and 4b respectively. These profiles have been used to infer the multivariate statistical distributions described before.

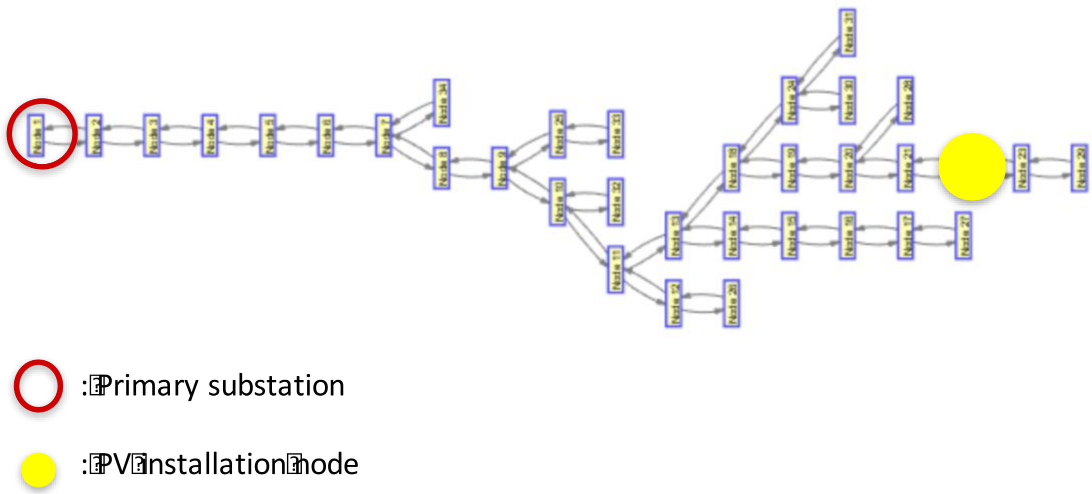
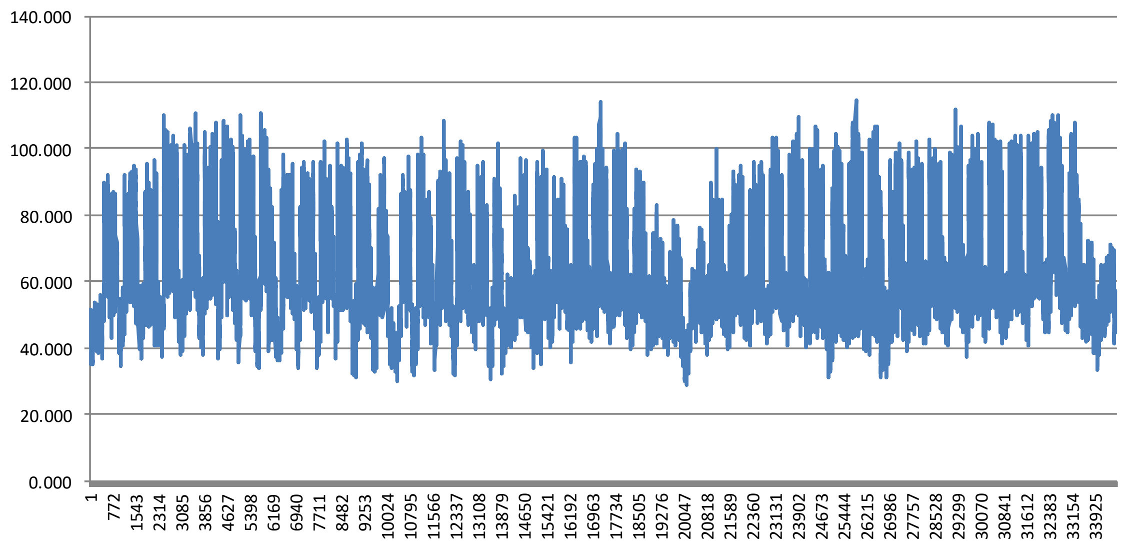
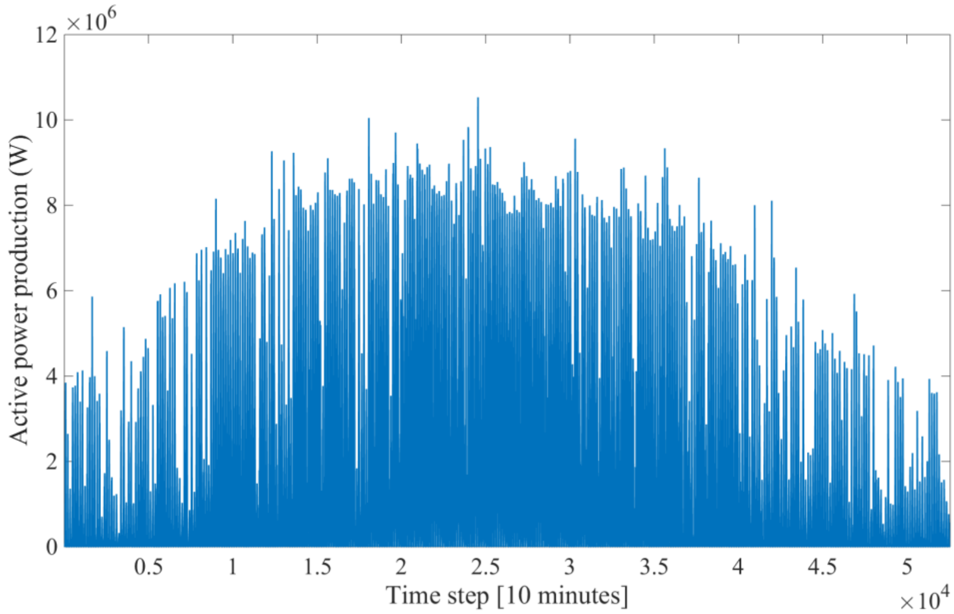


Figure 3: Topology of the Onnens 20kV feeder.



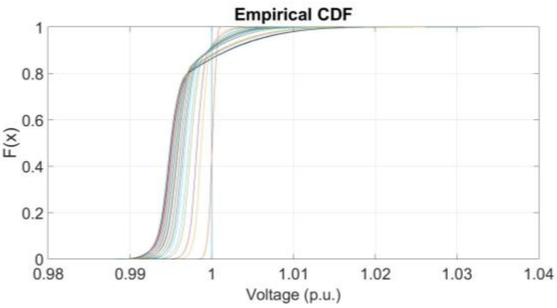
a)



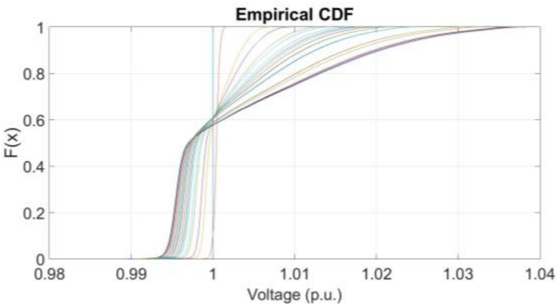
b)

Figure 4: Yearly aggregated load consumption (a) and PV production (b) for the Onnens feeder.

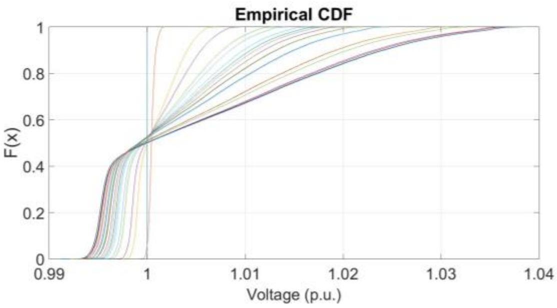
The steady-state security of the Onnens grid is assessed using PLF described above. The obtained Cumulative Distribution Function of the nodal voltage-magnitudes and lines' current are obtained using the PLF are depicted in Figures 5 and 6, respectively, for all the network nodes and lines. The results are clustered for the four seasons of the year.



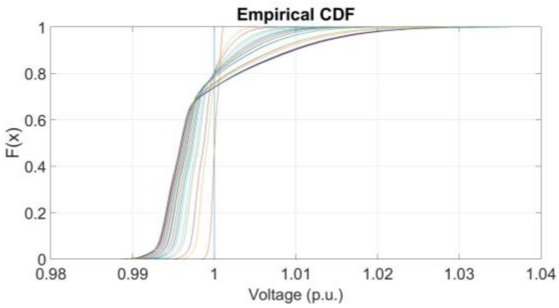
(a) Winter



(b) Spring

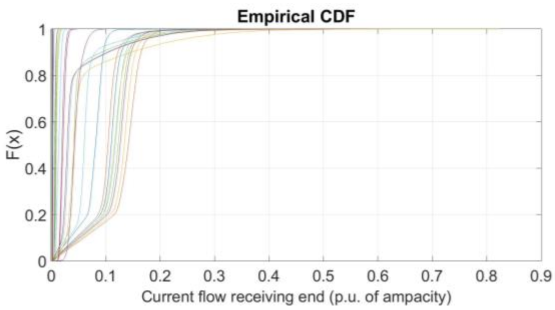


(c) Summer

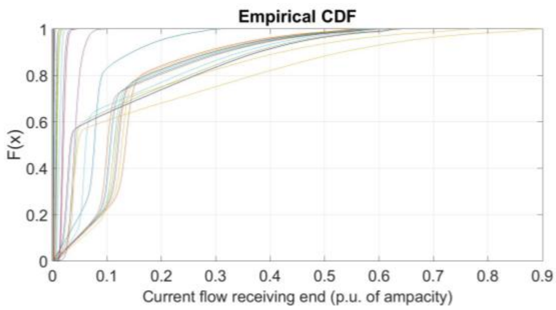


(d) Fall

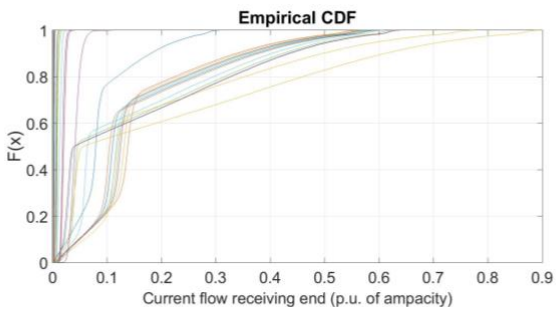
Figure 5: CDF of the nodal voltage magnitudes for Onnens feeder.



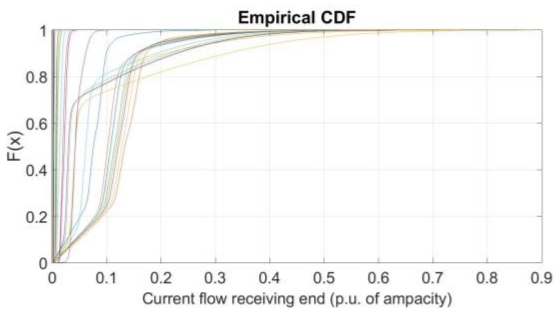
(a) Winter



(b) Spring



(c) Summer



(d) Fall

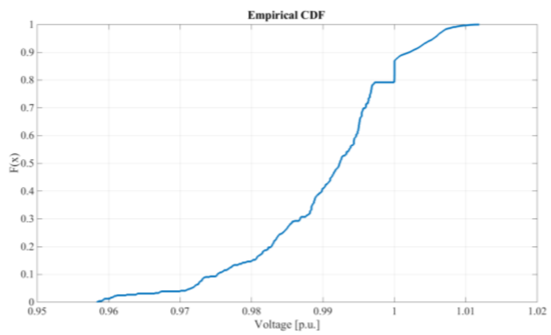
Figure 6: CDF of the lines' current of the Onnens medium feeder.

As it can be seen from Figure 5, the Onnens feeder will face over-voltages in 3 seasons: summer, spring and fall. Note that the standard upper bound for the voltage magnitude in Swiss medium voltage grids is 1.02 p.u.. Over-voltages (>2%) occur in these 3 season. Then, from Figure 6, we can observe that the network lines operate close to their ampacity limits during spring and summer periods.

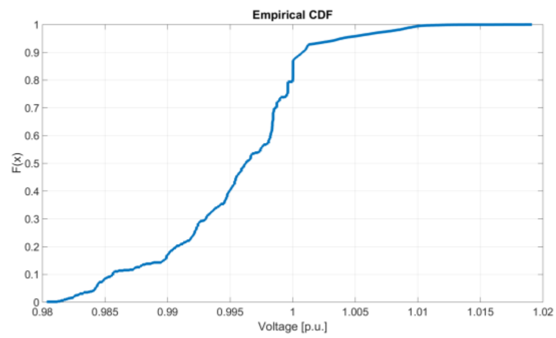
Study of the Rolle low voltage grids using the PLF process

The second grid is composed by six low voltage systems on the site of Rolle. For sake of brevity, we do not report the yearly profiles of the loads and PV generation.

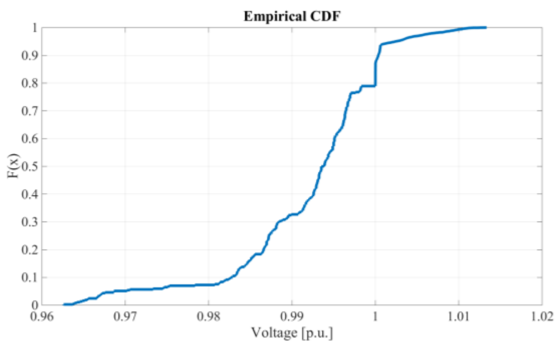
The CDF of the nodal voltage magnitudes for a given time slot are shown in Figure 7 (for sake of brevity, we do not report all the results). The lines' current and nodal voltage-magnitudes of all the six low voltage grids are within the safe operational margins for all the simulated scenarios. In particular, voltages are always between -10% and +4% of the rated voltages values and line currents largely lower than line ampacities. Note that these are low voltage grids and the acceptable limits for lower and upper bounds are -10% and +4%, respectively.



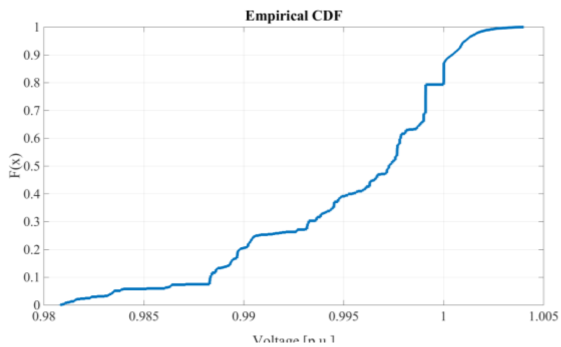
Martinet



Bourgois



Gare



Bourdonnette

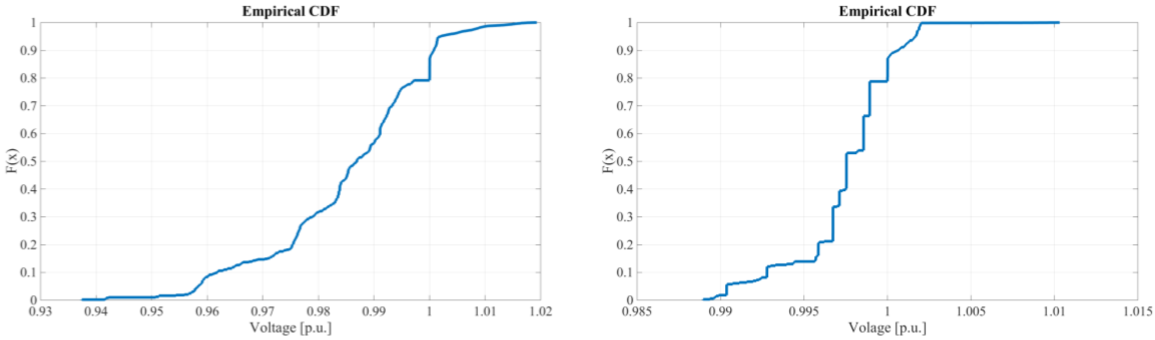


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Figure 7: CDF of the nodal voltage magnitudes for the targeted low voltage grids on the site of Rolle.

3. Impact

The results of the analysis carried out in this deliverable have two fundamental impacts. The first one is related to the setup of a standard analysis process to be used by FURIES utilities. The second is associated to the identification of the operational constraints of the two targeted electrical distribution networks. With particular reference to the case of Onnens, the analysis has quantified the probability to exceed the grid operational constraints for both nodal voltages and line currents. This analysis will be used to dimension, and locate, a suitable battery energy storage system in the Onnens grid (deliverable 1.4.4b). With reference to the Rolle grids, the analysis has shown that the inclusion of grid constraints in aggregation/control processes is useless since all the six grids do not exhibit violations of operational constraints. This result will impact the definition of the control processes expected to be deployed in this demonstration site.

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