D5.2 OPENTUNITY power flow developments (v2)

12 December 2025

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OPENTUNITYproject.eu

Deliverable details

Title	WP	Version
OPENTUNITY power flow developments (v2)	5	1.0

Contractual delivery date	Actual delivery date	Delivery type*	Dissemination**
M30 (June 2025)	M31 (July 2025)	R	PU

*Delivery type: R: Document, report; DEM: Demonstrator, pilot, prototype; DEC: Websites, patent fillings, videos, etc; OTHER; ETHICS: Ethics requirement; ORDP: Open Research Data Pilot.

Dissemination Level: **PU: Public; **CO**: Confidential, only for members of the consortium (including the Commission Services)

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Version	Date	Person	Action	Status***
0.1	12.05.2025	Álvaro Nofuentes (ETRA)	Table of Content	Draft
0.2	03/06/2025	Lucas Pons (ETRA)	Content added for ETRA module	Draft
0.3	24/06/2025	Dimitris Lagos, Themistoklis Xygkis, Orestis Darmis, Kyriakos Andresakis (ICCS)	Contributions for the ICCS modules	Draft
0.4	27/06/2025	Lucas Pons, Álvaro Nofuentes (ETRA)	Horizontal sections and last refinements for peer review.	Draft
0.5	03/06/2025	Sara Vieira (ANELL), Federico Giani (AEM)	Peer review	Draft
1.0	07/07/2025	Álvaro Nofuentes (ETRA)	Final Version	Final

***Status: Draft, Final, Approved, Submitted (to European Commission).

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Keywords

DSO, Topology identification, Topology detection, Low-cost Real-Time thermal rating, Dynamic Line Rating, State estimation, Fuse burn detection, Critical Point detection, DER impact

Executive Summary

This document presents the implemented and final version of the OPENTUNITY modules providing services and technologies for grid operators.

The summary and purpose of each of the modules is presented below:

Topology identification tool:

Aims to determine both the connections and line impedances, without knowledge of line infrastructure.

Topology detection tool:

The system operator knows the line infrastructure and their impedances and needs to determine the ones that are currently energized.

Fuse burn detection tool for early outage and islanding recovery:

In certain cases, the normal operation of a triphasic line gets disrupted when a fuse from one phase blows. The aim of the task is to detect the blown fuse through the monitoring of the voltage at end user level and the appropriate calculations.

Enhanced state estimation tool:

Aims to retrieve the unknown system state, that is, the complex voltages at all buses and connection points.

Critical point detection tool:

The aim of this tool is to detect critical points in a branch given the capacity limits of the different sections of cable in the same line.

Short term analysis of the impact of DER in the Distribution grid:

The aim of this tool is to study the voltage variations due to DER fluctuations that might impact the stability in the transient state.

Real-Time Thermal Rating (RTTR) tool:

The aim of this tool is to develop a Dynamic Line Rating algorithm based on weather condition estimation.

Each module is described in detail, focusing on their functionalities and the User Interface that will access those functionalities. A high-level overview of the complete developments can be seen in Section 3. **The modules presented have been integrated to the Advanced Distribution Management System (ADMS) developed by ETRA called ÉTER.** The RTTR module integration into ÉTER will be further discussed in the WP6.

Finally, the conclusion of the development performed and the next steps (linked to deployment and demonstration activities) are explained in the "Conclusions" section.

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2 INTRODUCTION

2.1 Purpose of the document

The purpose of this deliverable is to provide a clear explanation about the developments of Task 5.2 “Upgrading topology identification and state estimation” and Task 5.3 “Low-cost Real-Time thermal rating”. Firstly, an overview of how all the different modules and developments interact is provided and then, the detailed individual explanation is shown.

2.2 Scope of the document

The scope of the first version of this deliverable (D5.1) has been circumscribed to the technical description of the different modules developed under Task 5.2 “Upgrading topology identification and state estimation” and Task 5.3 “Low-cost Real-Time thermal rating”. In that deliverable, the description of the design and implementation of the modules is provided, together preliminary mock-ups of the User Interface.

However, in this deliverable, the scope is circumscribed on showing the functionalities of the final version of the modules and their User Interface, without the need of explaining again the design and implementation aspects.

2.3 Structure of the document

Apart from this introductory section, the current document is structured as follows:

The document initiates its content with a summary of all the developed technologies and how they interact in order to provide valuable functionalities to the Distribution System Operator.

Then, each of the modules are described and present a user’s manual.

The conclusion of the development performed, and the next steps (to occur in the demonstration activities of WP6) are explained in the “Conclusions” section.

At the end of the document, an annex is included, where relevant technical info that was not included in the first version (or it should be amended from it) is reported. This is necessary since the development phase of technologies like the ones developed in OPENTUNITY may evolve from its initial design in order to cover first feedback from end-users.

3 OVERVIEW OF THE DEVELOPED TECHNOLOGIES

This section presents the design and high-level architecture of the OPENTUNITY modules providing services and technologies for grid operators. The Figure 1: OPENTUNITY grid operator services architecture illustrates how these modules are related among each other and with the main distribution system components and applications.

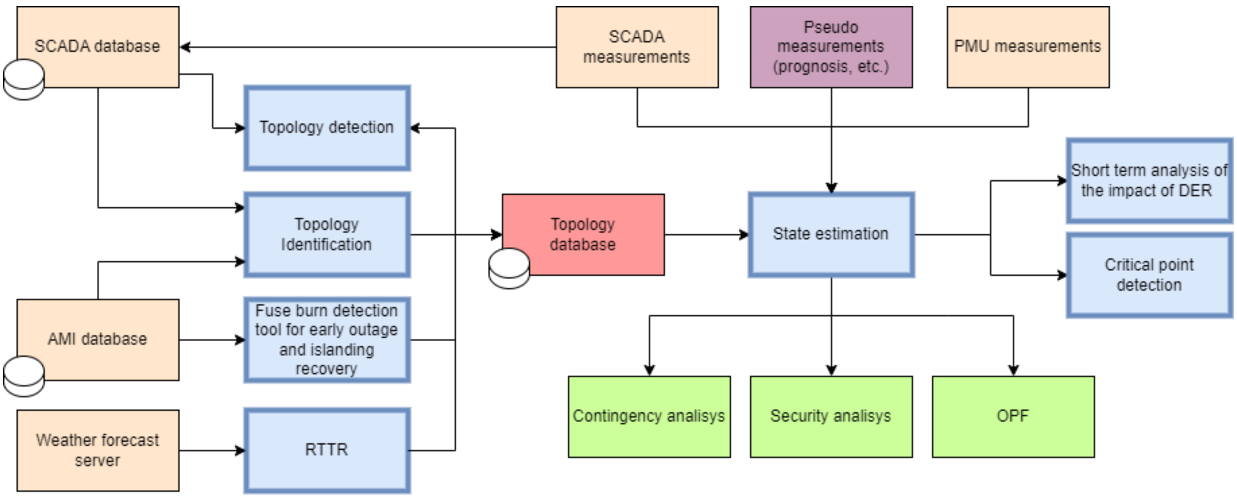


Figure 1: OPENTUNITY grid operator services architecture

The OPENTUNITY tools are marked in blue. Orange boxes represent data sources, like the SCADA or AMI databases. Green colour is for the existing services of the DSO not directly covered by OPENTUNITY tools but that can benefit from its results.

At the centre of the grid management is the topology database. This database contains the structure of the grid and the characteristics of its assets.

There are four modules in OPENTUNITY that modify the structure of this topology. Two of them, the **Topology detection tool**, and the **Fuse burn detection tool for early outage and islanding recovery**, aim at identifying errors or inaccuracies on the existing topology based on the analysis of the data received from the SCADA and AMI systems.

Conversely, the **Topology identification tool** aims to determine the structure and connections of the low voltage network without any previous knowledge, just by analysing the smart meters' data received by the AMI system. This could be used to define from scratch the topology during the initial deployment and configuration of a low voltage network.

The last module affecting the topology structure is the **Real-Time Thermal Rating (RTTR) tool**. The aim of this tool is to develop a Dynamic Line Rating algorithm based on weather condition estimation.

By making use of the topology and the measurements from SCADA and PMUs, two versions of **Enhanced state estimation tools** will be developed. One that will focus on predicting the state of the unknown pseudo-measurements by making use of the historical smart meter and SCADA measurements, and the other more focused on the analysis of PMU data and the study of the most beneficial deployment option of these assets for observability purpose.

The obtained state estimation results could be used for the typical management DSO tasks, like security analysis of the current and forecasted situation, optimal power flow calculation or contingency analysis. Two tools will be added to this set of functionalities. The **Critical point detection tool** aims at detecting critical points in a branch given the capacity limits of the different sections of cable in the same line and could be used to simulate extreme situations and assess the correct behaviour of the grid. The **Short-term analysis of the impact of DER in the Distribution grid** aims at studying the voltage variations due to DER fluctuations that might impact the stability of the grid by causing congestions or affecting the protection scheme.

Most of the modules presented have been integrated to the Advanced Distribution Management System (ADMS) developed by ETRA called **ÉTER.** ETER is a web application featuring several functionalities for the DSO operator. The tool is a complete framework for the operator, and the OPENTUNITY innovations have been added as complements and enhancements to the tool.

The ETER tool is a multi-tenant application. This software architecture is organized as a single instance of the application that server multiple, distinct customers, organizations or pilots, known as “tenants.” Each tenant’s data is logically separated and isolated within the application, so one tenant cannot access another’s information. However, all tenants use the same codebase and share the underlying infrastructure resources, such as servers, databases, and networking.

4 TECHNOLOGIES

4.1 Topology identification tool

4.1.1 Description

One problem that often affects the low voltage (LV) networks is the incorrect topological information. Such networks are far more complex than the MV and HV networks, because they are composed of a myriad of small cable segments that are deployed following the structures of cities and towns towards the different connection points. This structure must be reflected in the topology database of the system operator, but there are situations where this topology is not accurate or does not even exist and should be defined, for distinct reasons:

- Some LV networks were deployed many years ago, and the digitalization of these networks rely on schematics and diagrams that might be inaccurate.
- The topology may have been defined by the DSO with the support of a SCADA provider selected for the monitoring of the grid, but the related SCADA product might have been discontinued or outdated, so the topology database modification or the export to a new SCADA system might be problematic.
- LV network topology changes frequently due to normal power engineering activities aiming at reducing line losses, managing outages or accepting more intermittent distribution generators, but these operations might not be properly logged-in the topology database. This might end up with a topological structure completely different from the one stored by the DSO.

The **topology identification tool** will try to identify the LV network topology from scratch, just making use of the available LV data, mainly the smart metering data.

One of the duties assigned to the DSO is the collection of the power curves from the end users. This was historically done using electrical meters, but nowadays Smart Meters are almost ubiquitous, and this task is automatically done using advanced metering infrastructure (AMI) systems. Smart meters in the AMI system periodically collect data from energy users and send these data to the utility, including real/reactive power, voltage magnitude and energy consumption. Also, there are smart meters installed at the second side of each distribution transformer to measure the total power consumption of all users energized by this transformer, with the purpose of managing line losses. The **topology identification tool** (also known in literature as topological learning) will make use of the residential data at feeder buses received in the AMI to try to build the network topology from scratch.

There are different approaches in literature that investigate on the topic of topological learning. Most of them make use of the Voltage Correlation (VC). VC uses one of the most basic principles of electrical engineering. When a current flows through an impedance, a voltage drop occurs. Hence, in a power system, a similar voltage profile over time suggests that the two metering sites are closely connected electrically. Next image depicts this process:

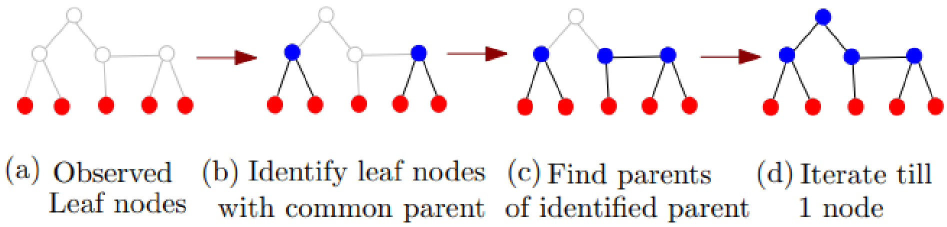


Figure 2: Grid reconstruction from leaf nodes measurements.

The identification of a common parent is not based on single time step values that might produce false positives, but on the analysis of the buses (leaves) measurements during a time period. The longer the period, the more accurate the association of leaf nodes is.

This process is running iteratively. In each step, several nodes can be associated with the same parent, and this parent node becomes a leaf for the next iteration (and the children are removed from the list of leaves). This process continues until an iteration is not identifying any parent relationship, meaning that no more associations will be identified. Theoretically, the process will rebuild the complete network, and all leaf nodes will eventually be linked in the topology, but since it depends on data observed, and might not contain enough variability in some leaves, an adjacency analysis would be needed to assess the completeness of the identified grid.

The process will take as inputs the historical measurements received from smart meters, including instrumental measurements voltage and current. These measurements are not normally provided by the smart meters, that normally restrict to active energy parameters, but there is the possibility to configure the DSO AMI to interrogate the assets for additional data. This process is known in DSO jargon as **test cycles** and requires the PLC aggregators in the grid to be configured appropriately. This is further explained in section **¡Error! No se encuentra el origen de la referencia.** - **¡Error! No se encuentra el origen de la referencia.** The next picture illustrates how the process behaves:

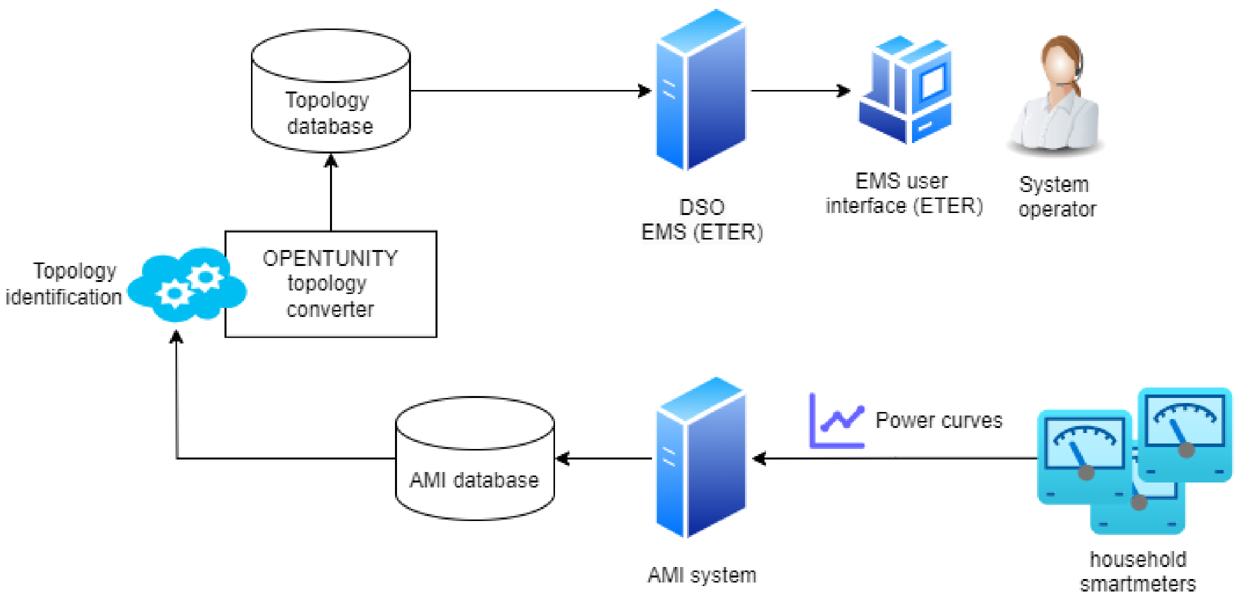


Figure 3: Network identification in context

The core of the process is performed in a service linked to the OPENTUNITY topology converter and described in deliverable [1]. This tool aims at transforming power network between different topological formats. The topology identification process has been modelled as an additional 'input topology' type, and therefore allows storing the topology in the format we prefer for further analysis:

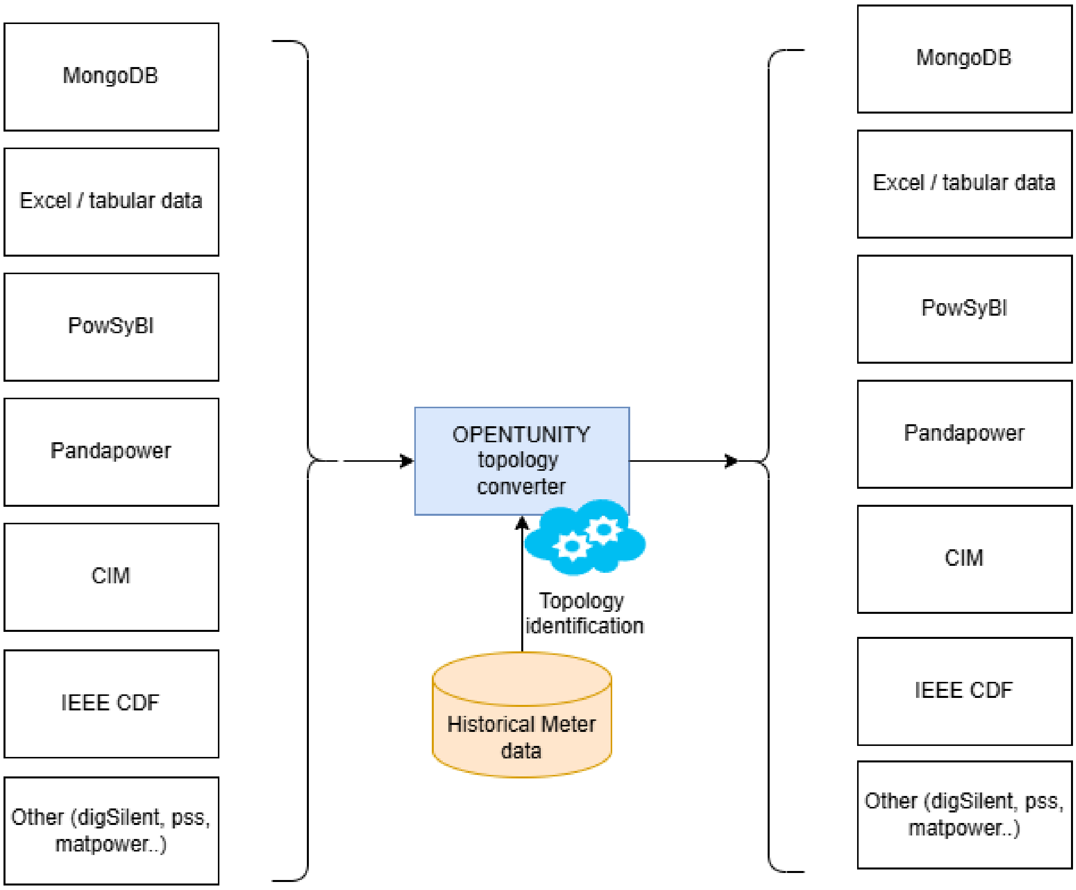


Figure 4: Topology identification results as an input of the Toplogy converter tool.

In this case, the topology converter tool input is specified with the details of the historical records to use for the analysis. The details are provided in the next section

4.1.2 User's Manual and Interface.

As it has been identified, the OPENTUNITY topology converter tool is used for identifying the topology. This tool is a command line tool that take some input parameters and produce a topology in a certain format. The signature of the process is as follows:

```
Starting Topology Alchemy...
['src/main.py', '--help']
usage: main.py [-h] --iFormat {powsybl,cim,tabular,pandahub,pandapower,mongodb,cdf,matpower,topologyIdentification}
               --input INPUT --oFormat {powsybl,cim,tabular,pandahub,pandapower,mongodb} --output OUTPUT
               [--activateTransliterate] [--processLV] [--deletePrevious] [--system SYSTEM] [--context CONTEXT]
               [--verbose] [--log LOG] [--defaultLayoutMV DEFAULTLAYOUTMV] [--defaultLayoutLV DEFAULTLAYOUTLV]

This program allows transforming topologies between different formats. It has been developed under the EU research project
OPENTUNITY

options:
  -h, --help            show this help message and exit
  --iFormat {powsybl,cim,tabular,pandahub,pandapower,mongodb,cdf,matpower,topologyIdentification}
                        Input format
  --input INPUT         Input file
  --oFormat {powsybl,cim,tabular,pandahub,pandapower,mongodb}
                        Output format
  --output OUTPUT       Output file
  --activateTransliterate
                        Transliterate Greek characters
  --processLV           Import LV network
  --deletePrevious      Generate delete commands for previous data
  --system SYSTEM       System id
  --context CONTEXT     Context
  --verbose             Increase output verbosity
  --log LOG             Log level
  --defaultLayoutMV DEFAULTLAYOUTMV
                        Default cytoscape layout for MV network
  --defaultLayoutLV DEFAULTLAYOUTLV
                        Default cytoscape layout for LV network
```

Figure 5: Signature process.

The value 'topologyIdentification' for the 'iFormat' input parameter configures the process to generate the topology from the historical voltages data file. In this case, the parameter 'input' must be provided with the location of the data file containing the historical measurements that will be used to reconstruct the topology. The rest of the parameters remains the same as for the normal topological conversion. **This process is described in deliverable D5.5. OPENTUNITY Grid integration methodology** [1].

The format of the input file is a CSV file with one row per time step and one column per smart meter. This is an example of this file:

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	timestamp	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10	SM11	SM12	SM13	SM14
2	01/01/2024 0:00	260,93	262,01	261,56	260,72	262,55	257,96	258,29	259,19	261,92	260,75	258,08	261,44	262,7	258,38
3	01/01/2024 1:00	258,5	257,54	260,33	257,99	262,1	261,86	260,39	260,42	259,01	262,46	260,09	259,49	262,25	258,92
4	01/01/2024 2:00	261,86	261,2	261,32	260,93	258,2	262,25	260,99	262,88	259,1	262,52	257,78	262,46	260,27	261,38
5	01/01/2024 3:00	260,42	258,2	259,76	257,15	258,05	262,97	257,51	257,3	258,53	257,69	259,73	260,63	259,16	261,71
6	01/01/2024 4:00	261,17	262,37	261,32	257,24	259,22	257,87	262,88	259,19	257,72	260,15	257,12	257,96	260,9	258,56
7	01/01/2024 5:00	260,18	261,14	260,12	257,84	259,79	262,46	257,09	262,19	259,94	262,88	258,38	257,33	262,61	262,61
8	01/01/2024 6:00	259,04	261,5	260,57	259,52	257,33	261,32	260,72	258,29	258,68	257,93	259,88	260,45	258,92	259,82
9	01/01/2024 7:00	258,56	261,92	259,94	259,85	257,42	259,4	259,88	260,6	257,42	261,68	259,37	257,57	262,97	262,34
10	01/01/2024 8:00	260,48	261,02	258,26	262,49	259,34	260,09	260,33	262,31	257,93	258,77	260,63	258,14	258,62	261,2
11	01/01/2024 9:00	257,63	258,38	262,52	260,12	258,89	257,63	259,4	261,74	260,18	261,47	258,38	259,82	261,11	259,46
12	01/01/2024 10:00	259,22	261,5	261,08	259,1	259,7	261,83	257,15	262,79	261,59	260,66	257,42	257,96	260,75	261,5
13	01/01/2024 11:00	262,01	262,88	257,81	260,18	258,62	262,43	260,48	259,52	262,07	259,67	258,35	260,87	257,12	262,49
14	01/01/2024 12:00	257,84	259,76	261,32	262,49	257,57	262,67	259,79	261,71	262,73	259,07	258,56	262,31	258,92	262,49
15	01/01/2024 13:00	257,48	261,17	260,15	260,99	258,29	259,01	259,46	258,98	258,98	257,39	261,38	258,32	259,97	262,46
16	01/01/2024 14:00	258,32	259,22	262,76	259,22	262,61	257,36	258,32	257,27	259,31	260,87	260,75	260,21	258,92	257,75
17	01/01/2024 15:00	261,62	261,59	258,62	261,8	260,15	260,72	259,1	260,21	257,18	260,96	261,71	260,33	262,7	260,9
18	01/01/2024 16:00	261,59	258,41	262,82	257,87	257,03	261,8	261,71	260,3	260,15	258,77	260,81	258,14	257,66	260,81
19	01/01/2024 17:00	257,96	262,55	259,76	257,24	258,38	259,79	261,44	262,46	261,83	258,26	258,86	259,55	259,73	262,46
20	01/01/2024 18:00	257,87	262,64	261,8	257,51	259,28	260,93	259,7	259,19	262,55	258,29	259,91	261,17	261,98	262,1
21	01/01/2024 19:00	259,4	261,83	261,29	262,04	262,52	257,66	258,47	261,74	262,64	260,87	261,17	260,57	257,72	260,87
22	01/01/2024 20:00	257,66	258,8	262,19	260,51	258,5	258,02	260,18	258,14	257,51	258,65	262,31	259,01	259,58	258,17
23	01/01/2024 21:00	261,47	257,15	261,77	257,54	258,86	257,87	258,95	259,49	258,62	259,28	258,47	259,34	257,24	259,4
24	01/01/2024 22:00	260,96	259,04	257,24	259,07	260,12	262,1	257,12	261,26	261,26	257,15	261,53	258,62	259,13	261,95
25	01/01/2024 23:00	260,57	259,28	259,31	260,69	260,96	262,88	262,97	260,93	262,97	258,47	258,56	258,83	257,63	257,54
26	02/01/2024 0:00	261,2	260,33	260,15	261,74	258,47	257,96	259,37	259,52	261,2	260,96	259,52	260	259,22	258,92
27	02/01/2024 1:00	262,73	258,26	259,55	261,29	262,19	261,17	260,27	260,87	257,36	257,24	257,24	262,1	257	260,06

Figure 6: Example of voltages file CSV

This is an example of the whole process running:

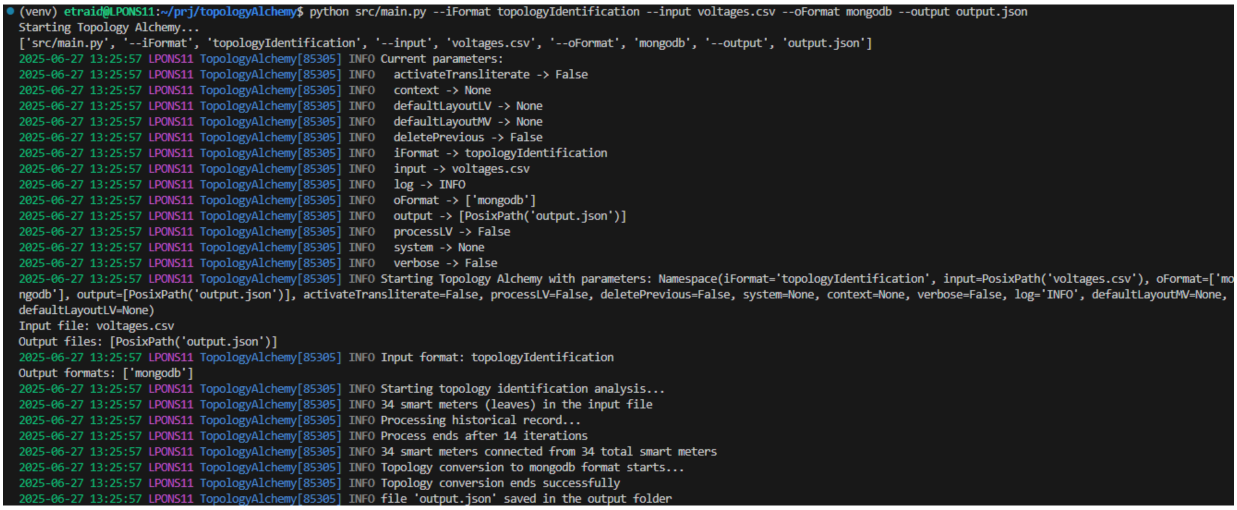


Figure 7: Example of complete process running.

The topology is stored in a JSON file that can be imported into a MongoDB database and opened in ETER tool.

4.2 Enhanced state estimation tool

4.2.1 Description

Power system state estimation (PSSE) is a crucial function within the energy management system (EMS), offering operators reliable snapshots of the operating system conditions based on real-time field measurements [2], [3]. In general, a state estimation (SE) module is capable of converting unrefined measurement data into structured information about the system state. For a power grid, knowing its real-time state requires estimating two key components

a) Its operating topology, i.e., the configuration of buses (nodes) and their interconnected lines (branches), and
b) Its state vector, which typically comprises either the positive sequence complex bus voltages or branch currents [4]. To discriminate the individual problems, the former one is referred to as topology identification (TI) and described in section 4.1 - Topology identification tool. Using the estimated topology and state vector, all the other grid variables (mainly referring to active/reactive power flows and injections) can then be evaluated, thus, providing the operators with vital insights into system behaviour. Concisely, the SE output can be exploited for real-time grid operation and control, e.g., volt-var optimization, fault detection, transmission-distribution interface coordination, cybersecurity etc., and planning tasks, such as proactive decision-making, contingency analysis, support of energy markets, forecasting, etc [5].

Since its introduction at late 1960s by Schweppe, PSSE has been formulated and solved as a model-based optimization problem [6]. Specifically, a measurement model based on Kirchhoff's circuit laws has been employed to represent the measured electrical quantities as functions of the state vector, while also incorporating the associated measurement errors. By applying maximum likelihood estimation (MLE) and assuming these errors follow a normal (Gaussian) distribution, the SE problem amounts to a weighted least-squares (WLS) task [3], [6]. Given that the measurement model is generally nonlinear, the WLS task can be iteratively solved using the Gauss-Newton algorithm.

The WLS method has long been the most widely employed approach for PSSE in energy control centers (ECC) at power transmission level [3], [4]. Moreover, it remained a focal point of related academic research until early 2010s. Research efforts primarily aimed to optimize PSSE performance to meet the rigorous standards required for real-time transmission system monitoring, while also developing viable distribution system state estimation (DSSE) algorithms, since the medium and low voltage (MV, LV) parts of the power grids have practically been unmonitored due to their passive behaviour [7]. This scarcity of measurements problem for state estimation calculation can be addressed using various techniques. This section presents one such technique: **ML-assisted estimation of statuses from unmonitored injections**. The next section describes an alternative technique: **Enhancement in the DSSE through the installation of PMUs and micro-PMUs in selected network locations**.

Given a limited set of power measurements acquired by supervisory control and data acquisition (SCADA) and distribution automation systems, state estimation aims to recover the unknown system state, that is, the complex voltages across the network. To enhance observability DSSE has to rely on the so-called **pseudo measurements** [8], that can be generated via load and generation forecasting tools. In this OPENTUNITY tool, the pseudo measurements generation technique for magnitudes such as the forecasted loads and voltages is postulated via deep neural networks (DNNs), that are capable of capturing complex nonlinear dependencies present in time series data.

The next diagram illustrates the different time horizons covered by the state estimation, including what measurements are available in each case[1]:

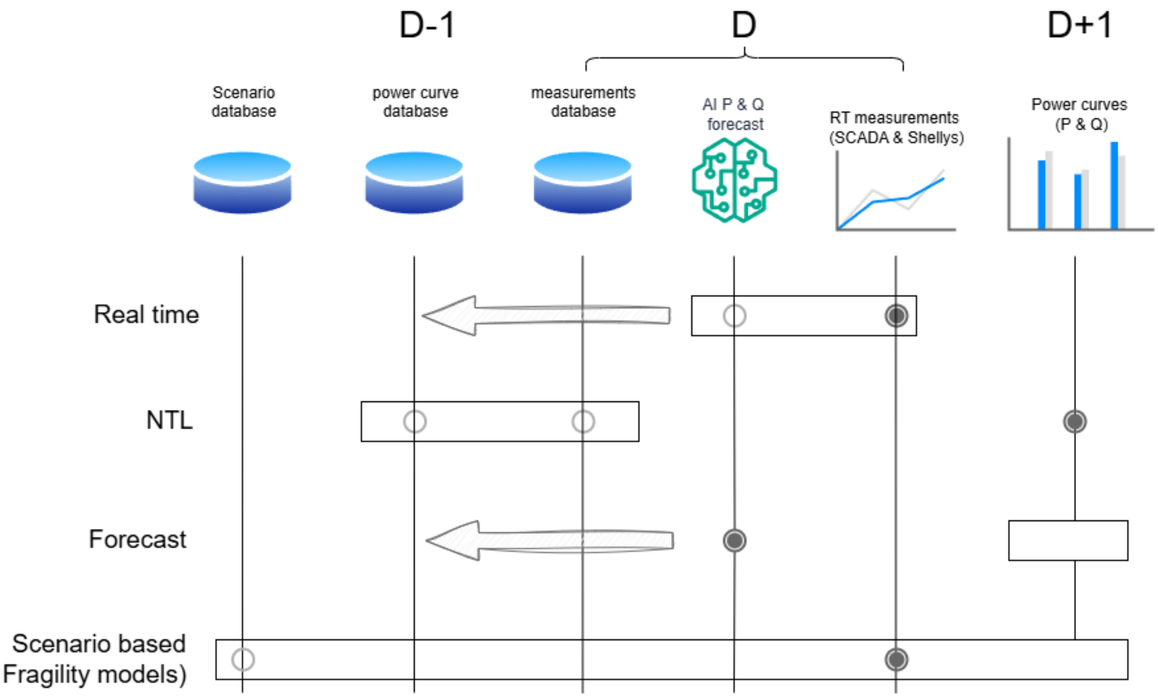


Figure 8: Time Horizons covered by State estimation.

The columns D-1, D and D+1 refer to the previous, current and next day respectively. During current day (D) power curves from smart meters are not available (they will be at D+1), so the power curve database contains D-1 data. This makes impossible the usage of power curve data for real time state

[1] Non-Technical Losses Module (NTL) is reported under Deliverable 5.4.

estimation, so the calculations must rely on P & Q forecast (pseudo measurements) and available RT measurements.

NTL use state estimation (explained in Deliverable 5.4) calculated for past periods, so it runs in D+1. At this moment, the power curves will be available and thus the use of pseudo-measurements is not required, but just historical power curves and SCADA data are required.

Forecasting state estimation is as subset of the real time calculation where there is no real time available, and the estimation goes away from now.

Finally, scenario-based state estimation is based on snapshots of the system where the operators can manually modify the measurements to perform experiments.

4.2.1 User's Manual and Interface.

In this section, it is described how the state estimation is presented within the OPENTUNITY ETER tool user interface.

In order for this to work the operator is required to log in to the system using its credentials:

For security reasons, the user credentials are stored in an independent keycloack identity server accessible through the internet.

After entering, the user can navigate to different sections of the application, like main dashboard, assets' portfolio, geographic map or topology view:

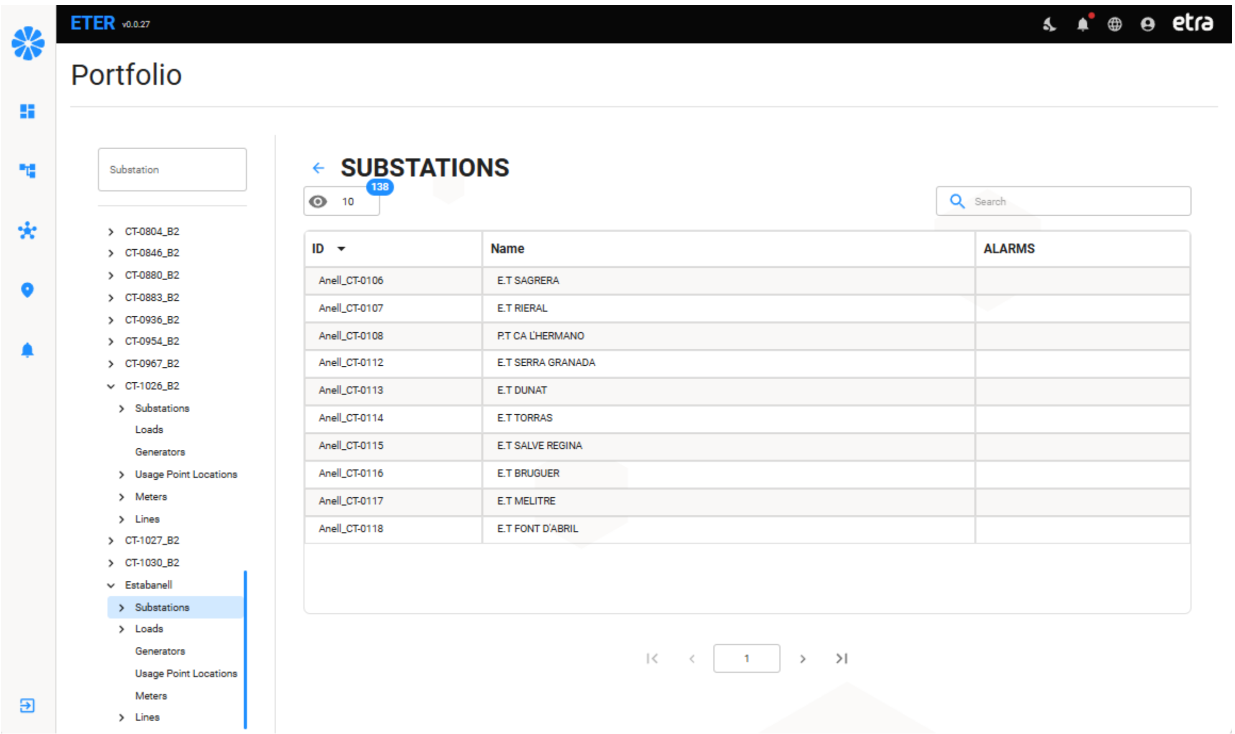


Figure 9: Example of portfolio management in the ETER tool.

Most of the OPENTUNITY functionalities have been included in the topology view. This is an example of the Spanish pilot topology view:

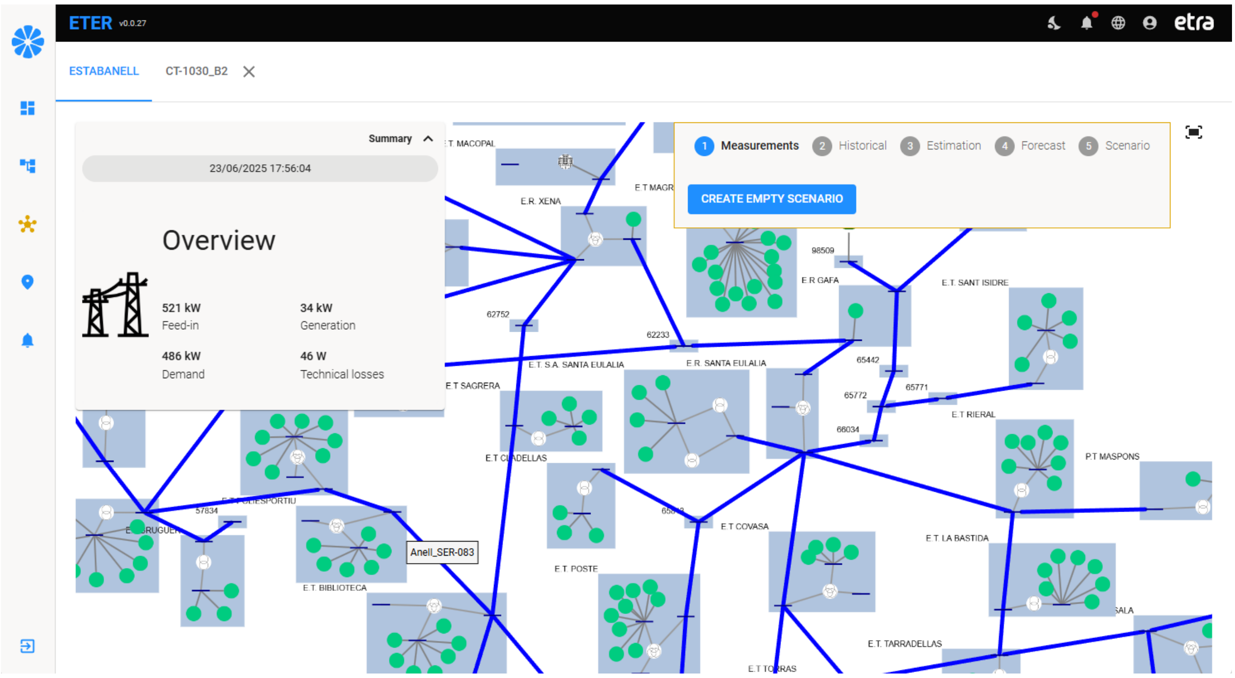


Figure 10: MV grid of Spanish pilot site

This section presents the topology of the grid. The enhanced state estimation results are presented in this interface in different ways, depending on the visualization mode selected by the operator. The descriptions of the visualization modes and how the visualization adapts to it are described within this section.

There are different areas in this interface:

- On the **top** there are tabs to navigate through the open grids. Initially only the medium voltage grids will be presented, but when a low voltage bus is selected in the MV topology, its related LV grid can be opened in a new tab by clicking the corresponding button. The LV grid tabs can be closed, but the MV is always present. This is an example of an LV grid in the interface:

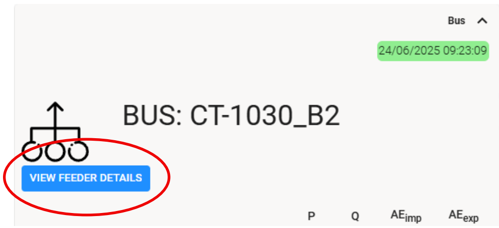


Figure 11: Button for opening LV grid visualization

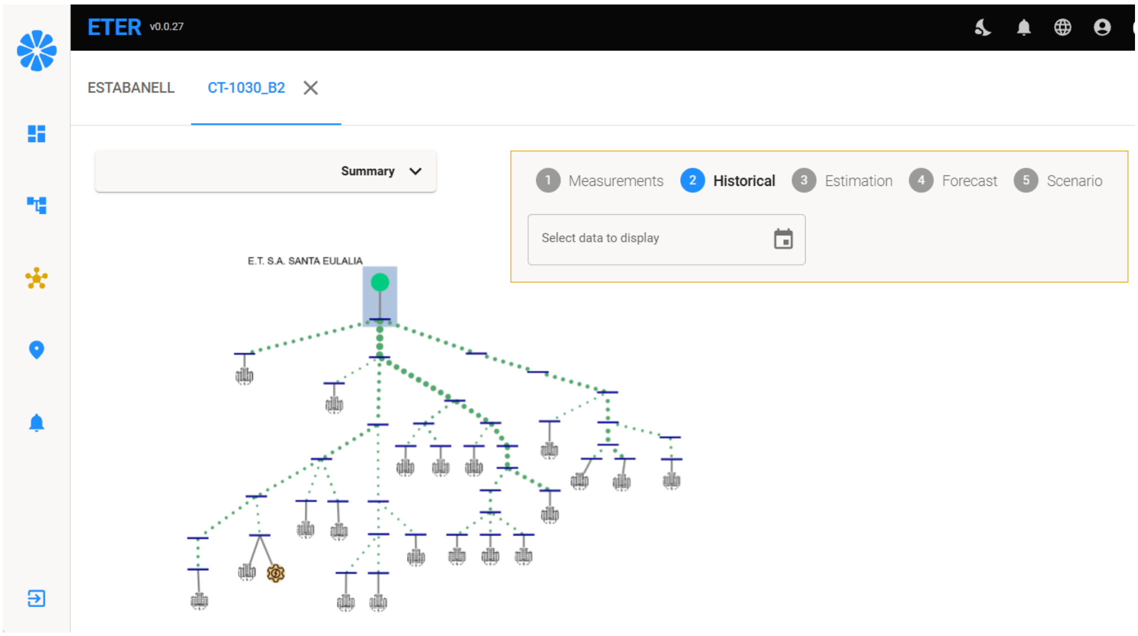


Figure 12: LV grid defined by substation 1030 in Spanish pilot site

Opposite to the MV grid, the LV does not contain transformers and usually contains one single substation and a radial structure.

- In the **center** of the screen, the topology is presented, including the conductors and the different nodes. The following types of topological nodes are shown in this section:

Table 1: Types of topological nodes

Representation	Type of element
	Substations. Depicted as blue boxes that might contain other elements
	Buses. Depicted as horizontal bars
	Connections to other networks: Might be connections to HV, MV or LV grids, depending on the current visualization. They are depicted with green circles inside the substations
	Two and three windings' transformers
	Usage points. Geographical location where one or more supply points can be connected
	Distribution side generators
	Switches and protections

- The conductors (lines and wires) connect different elements in the topology, like buses, supply points, etc. If the currently selected visualization type contains information about the power flows it is also displayed in the topology by means of animated dotted lines that represent the flow of energy from one bus to another. The width of these lines gives an indication of the amount of energy transmitted by each line. The line color also provides information about whether the line is congested (red color), close to be congested (yellow color) or in a safe state (green color):

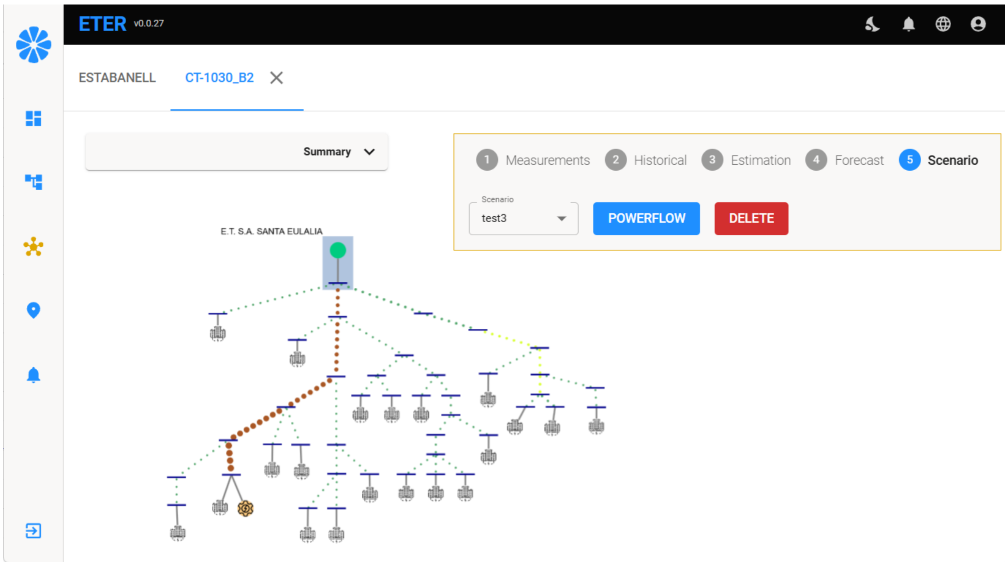


Figure 13: Lines with different levels of congestion.

The substation elements are contained in the substation object (within the blue box).

When the grid topology is first accessed, a distribution of the elements in the topology is generated according to a predefined layout that tries to position the elements in the best possible way. In case the elements contain geographic locations, these locations are used and a geographic distribution layout is used.

The elements in the topology can be moved freely by dragging and dropping them. This let users adapt the topology layout according to their needs. The distribution of the elements in the topology is stored on each change.

- By clicking on the different elements, its details will be shown in a **dialog floating at the top left** of the screen. Depending on the type of element clicked, the information presented will change:

  When clicking on the background on the topology, the whole grid is selected, and the summary is presented:

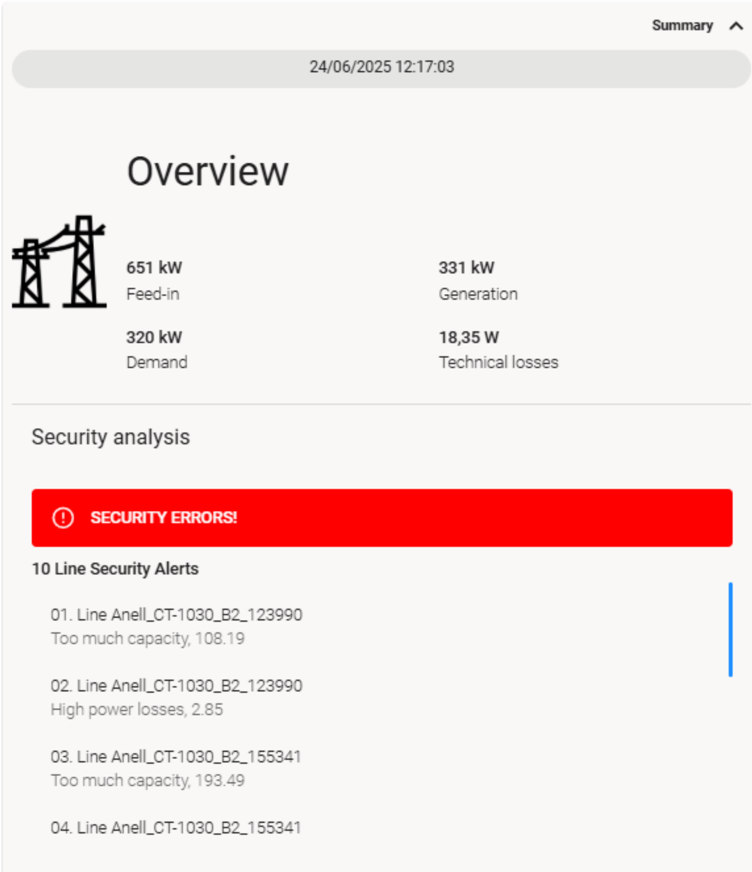


Figure 14: Grid state summary

In case the selected visualization type contains power flow information, the following information is presented:

- The aggregated measurements of the whole grid, as the amount of power injected from external networks and the amount of power consumed and generated internally.
- The result of the security analysis in the steady state. It is presented as a list of problems detected: line congestions and voltage deviations above thresholds.

By clicking on a substation, the amount of active and reactive power delivered by the substation is shown:

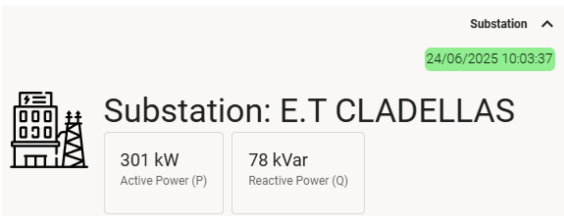


Figure 15: Substation details

Every details' dialog presents at the top right position an indication of how old the data shown is. This will help the operator better understand and interpret the data presented. This is necessary and relevant, because the power flow and state estimation calculation can take some time to generate results or could even fail and not update the measurements. Next is the bus detailsbus dialog:

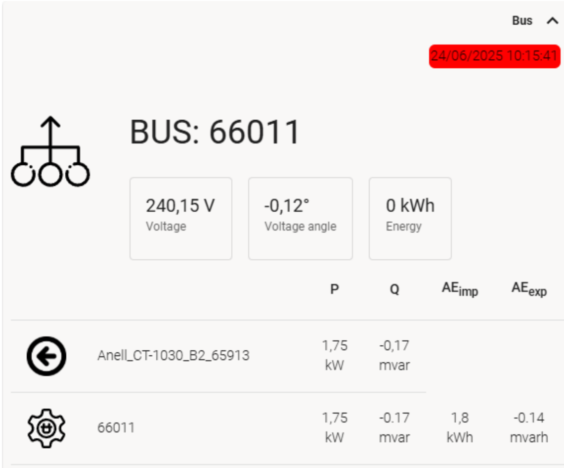
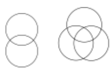


Figure 16: Bus details

On top of the dialog there are measurements for the current visualization mode (voltage, voltage angle and energy)

Below there is a list of elements connected to the bus. The following types of elements can be connected:

Table 2: Type of elements that can be connected to the bus

Representation	Element type
	Lines or wires connected to the bus.
	Supply points (loads)
	Distributed generation
	transformers

For each one, the active and reactive power measurements are shown (if available).

The next type of element that can be represented are the lines between buses:

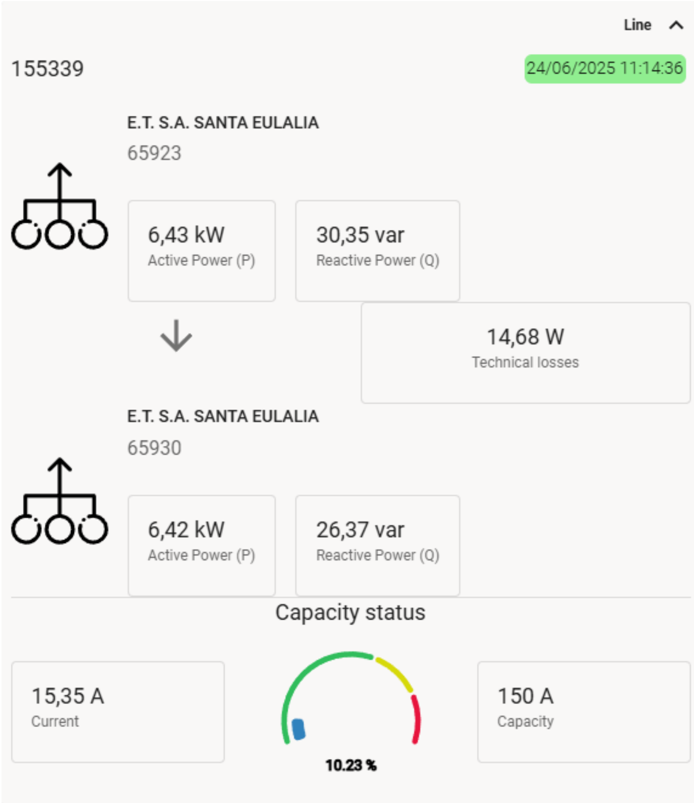


Figure 17: Line details

Here the two buses are represented, each one with its corresponding active and reactive power. The technical losses are calculated from the amount of energy flowing through, the characteristics of the line and the length of the line.

At the bottom part, the capacity of the line is represented as the maximum electrical current that can flow through the line. The instantaneous usage percentage is also presented in a gauge, as an indicator of the level of stress of the line.

Next selectable item in the topology is the usage point location. It is a geographic location that acts as a container of supply points. The representation is the following:

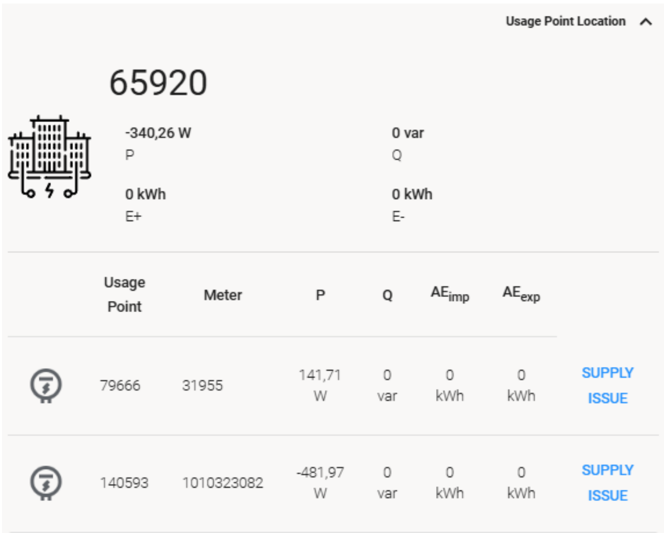


Figure 18: Usage point location details

The list of supply points in this usage point location is presented at the bottom. For each one, active and reactive power is presented. The aggregation of the measurements for all supply points is presented at the upper part of the dialog.

- At the top right side of the dialog, the type of visualization of the topology can be changed, and the data presented in the topology will adapt to the selected visualization. There are five types of visualizations available,

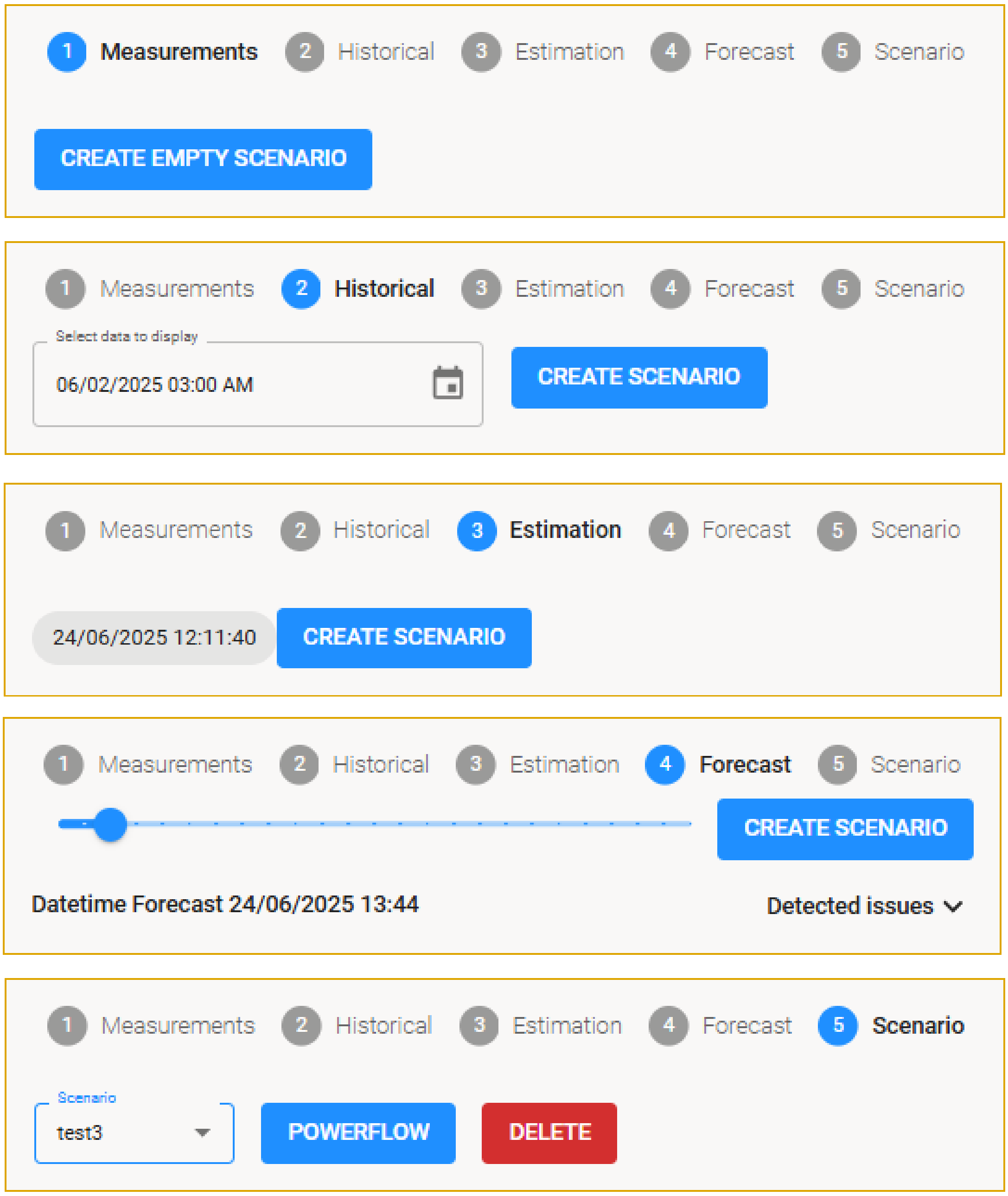


Figure 19: The five available visualization types

- **Measurements**: It simply presents the topology, and the last measurements received for each of them.
- **Historical**: It features a date-time picker that lets user select past moment (with hourly resolution). If there are power flows calculated for the selected moment, all information presented in the main topology and the detail viewers present the appropriate power flow information.

- **Estimation**: Presents the most up-to-date state estimation of the grid.
- **Forecast**: It features a slider that lets user select any of the upcoming 24 hours. Upon selection of an hour. If there are power flows calculated for the selected hour, all information presented in the main topology and the detail viewers present the appropriate power flow information.
- **Scenario**: If lets user experiment with the scenarios. This is further explained in section 4.6 - Critical point detection tool.

4.3 Enhanced state estimation tool (Greek demo version)

4.3.1 Description

The enhanced State Estimation (SE) from Greek tool integrates a Distribution System State Estimation (DSSE) module to ensure grid observability at the Greek demo site, which features an active distribution network. It monitors the real-time operating state of the system at the **medium-voltage (MV) level**—from the primary substation in Markopoulo to customer-level service transformers—**via estimation of network topology and nodal complex voltages.** Given the limited availability of real-time measurements at the distribution level, the tool leverages learning-based DSSE models based on Deep Neural Networks (DNNs), which eliminate the requirement for measurement redundancy present in conventional methods such as the Weighted Least Squares (WLS) model. To support this, a limited number of optimally allocated Phasor Measurement Units (PMUs), selected using a Random Forest (RF) algorithm, provide the necessary synchrophasor input data.

In this framework, the enhanced SE tool provides 3 DSSE-oriented services:

i. topology identification (real-time monitoring function)

ii. state estimation (real-time monitoring function)

iii. meter placement (design task)

The designed DSSE approach was implemented using 1) the MATLAB software (release version 2024a) along with the open-source toolbox for electric power system simulation and optimization MATPOWER (release version 7.1), to generate the training dataset for DNN models, and 2) the Python programming language (release version 3.10) along with the libraries Keras, TensorFlow and scikit-learn, to develop, train and evaluate the models.

In the sequel, the technical specifications of the data-driven framework for the Topology Identification (TI) and State Estimation (SE) functions, as an integrated process of the DSSE module, are detailed. The overall processing pipeline of the DSSE tool is depicted in Figure 20.

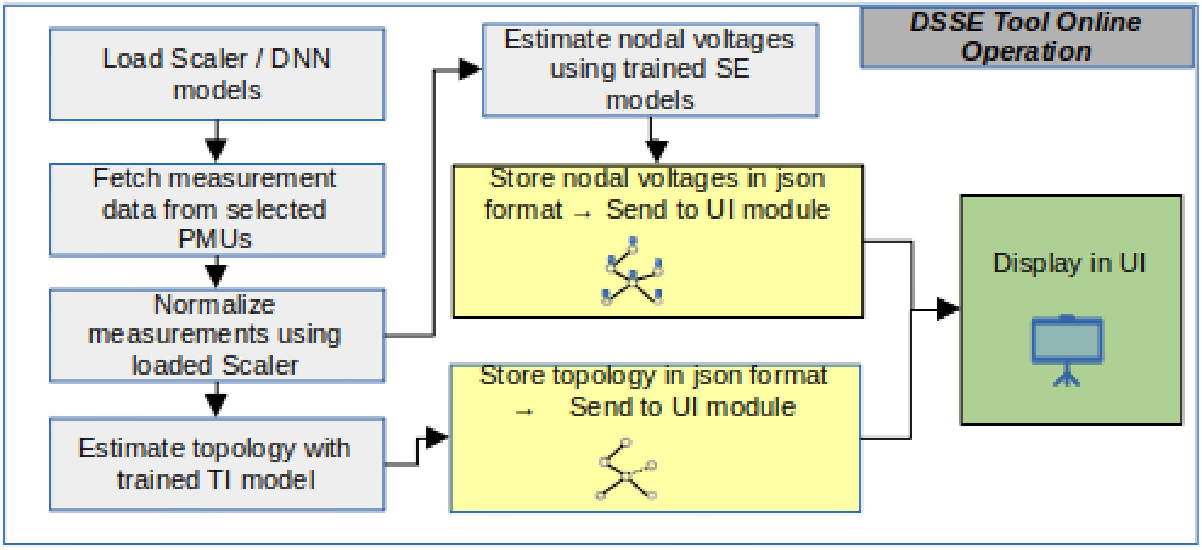


Figure 20: Data processing flow diagram of the DSSE tool

The NNs used for TI and SE are pre-trained on a large dataset. Their weights and architectures are predefined and stored inside the framework's directory, along with the normalization module (scaler). The DNNs are stored in *.h5* file format and the scaler is stored as a *.pkl* file.

First, the 3 separate DNNs used for topology, voltage magnitude, and voltage angle inference and the normalization module are loaded. The module then creates a connection to the local database (SQL Server database management system, deployed in the same LAN with the tool) containing real-time PMU data, and executes a query to retrieve all relevant measurements (according to their timestamps) to be used as an input to the trained TI and SE models. According to the results of the PMU placement design task, the DNN inputs expect PMU measurements, i.e., node voltage and line current phasors (magnitude and angle), from three nodes: 22, 44, and 48 (see Figure 25 for additional details).

Once the PMU data is retrieved and both the DNN models and the scaler are loaded, the measurements are preprocessed into a suitable format for normalization and passed through the scaler. This normalized input is then used by all DNNs. The first DNN produces a one-hot encoded output with two probability values — each corresponding to a possible topology. The framework selects and returns the topology with the highest probability. The remaining two DNNs each output a value for every node: an estimate for the voltage magnitude and one for the voltage angle. The final JSON (JavaScript Object Notation) response returned to the front end includes:

- the (common) timestamp value of the measurements,
- the topology inferred by the first DNN denoted by either "T1" or "T2", depending on whether the line between nodes 44 and 48 is disconnected or in operation, respectively, and
  a list containing each node index, along with its estimated voltage magnitude and phase angle.

4.3.2 User's Manual and Interface.

The web-based end-user interface is implemented using the *Streamlit* Python library and is depicted in Figure 21. In the first UI Tab, a near-real-time MV-network visualization and monitoring dashboard provides the TI and SE outputs (see the ribbon-style layout at the top-left of Figure 21). The second

Tab provides information pertaining to the proposed meter placement scheme. When the UI is initialized, a short loading time is expected, as it constructs the *pandapower* network model, applies specific node metadata, and initializes the topology to "T1". The JSON file containing the most recent estimated topology and complex nodal voltages is then accessed by the UI module automatically, upon completing the DNN inference; thus, the user need not make any specific actions to refresh the interface[2].

The "SE & TI Results" Tab features a graph-based node-branch network representation[3]. Each node—excluding zero-injection nodes—is labelled with its identifier, corresponding to the service transformer code used by HEDNO. If photovoltaic units are installed at the low-voltage (LV) side, the label includes the indication "(PV)." MV customers are identified by the prefix "SUB" in their names. The network operates either in a strictly radial configuration or with a single loop enabled by closing the switchable branch between nodes 44 and 48 (Figure 21 and Figure 22).

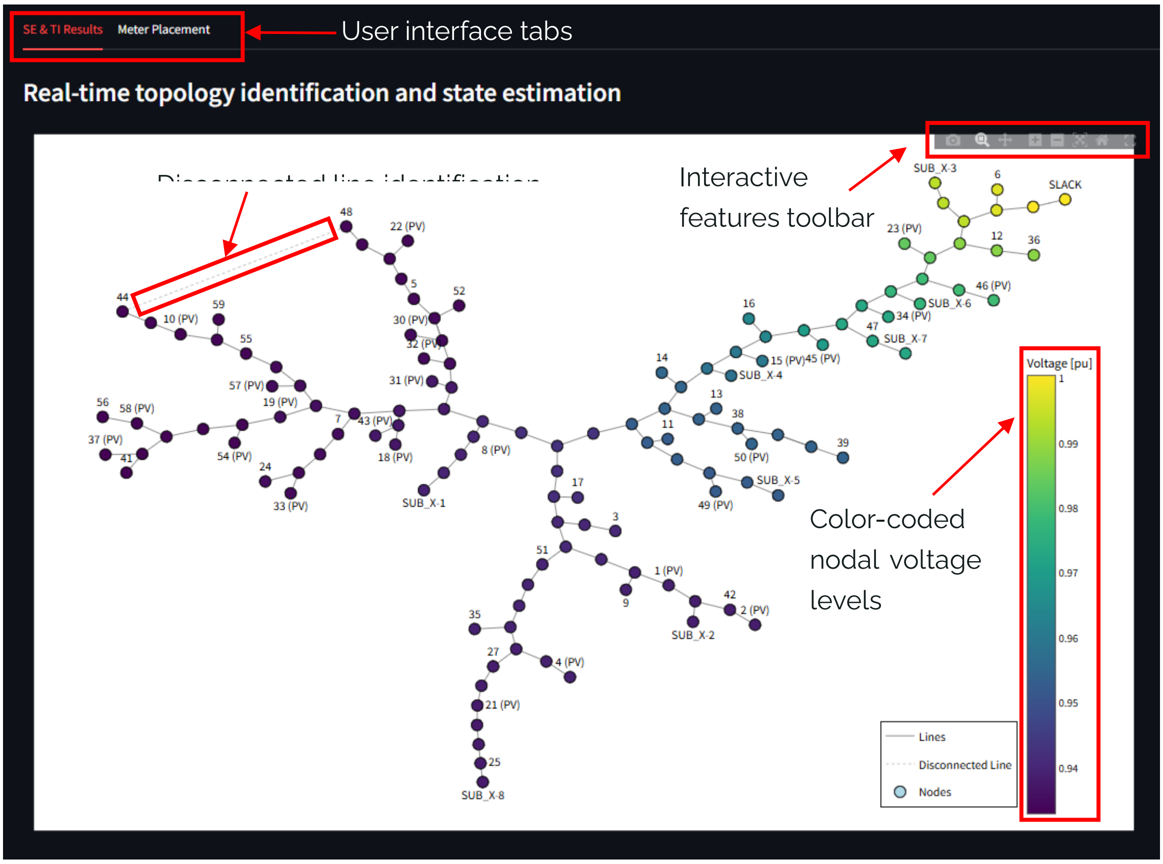


Figure 21: Topology and state estimation end-user interface with disconnected line

[2] It is noted that while PMU data are streamed at millisecond resolution, the tool processes snapshot-based inputs extracted at a reduced rate—approximately once per minute, in line with the agreement with HEDNO. DNN inference on each snapshot is completed within a few seconds, after which the UI is promptly updated to reflect the new results.

[3] The *plotly* Python library is used to represent the network graph, as well as store and customize the properties of the figure traces (node colors, label positions, legend entries, etc.).

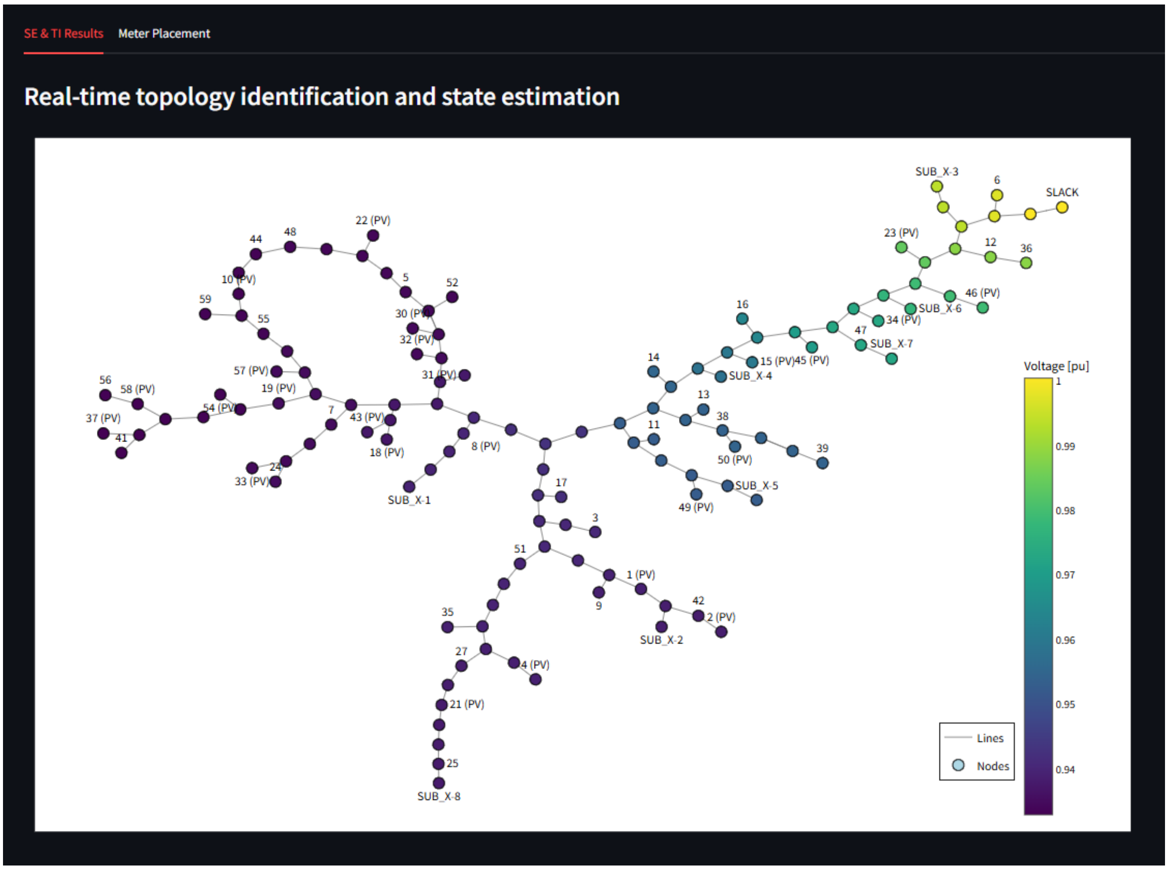


Figure 22: Topology and state estimation end-user interface with no disconnected lines

The TI output is made available to the user by altering the network representation in real time. The legend on the bottom-right of the UI is also altered dynamically, according to the estimated topology. To clarify these features, observe that in Figure 21 the network graph and the legend indicate that the line connecting nodes 44 and 48 is disconnected, while Figure 22 shows an overview of the UI with the same line in operation. Interactive features include a full-screen mode, the capability to save the current operating snapshot locally as an image, zoom-in and zoom-out functionalities, and an on-mouse-hover tooltip that provides branch properties (branch index, line length in km, resistance and reactance in Ohms/km). The tooltip is specifically demonstrated in Figure 23.

The UI is also tasked with assigning the estimated voltage phasors to the nodes of the network graph. High-level information for nodal voltage levels is made available to the user via color-coding of each node that matches the estimated voltage magnitude (see the colour bar on the bottom-right of Figure 21). This feature guarantees that the user always has a real-time monitoring dashboard available to quickly identify voltage deviations. With this overview as reference, the user is able to zoom in any part of the network and/or hover on any node to trigger a tooltip with detailed information (node name, nodal voltage magnitude in kV and angle in degrees, and transformer nominal capacity), as depicted in Figure 24.

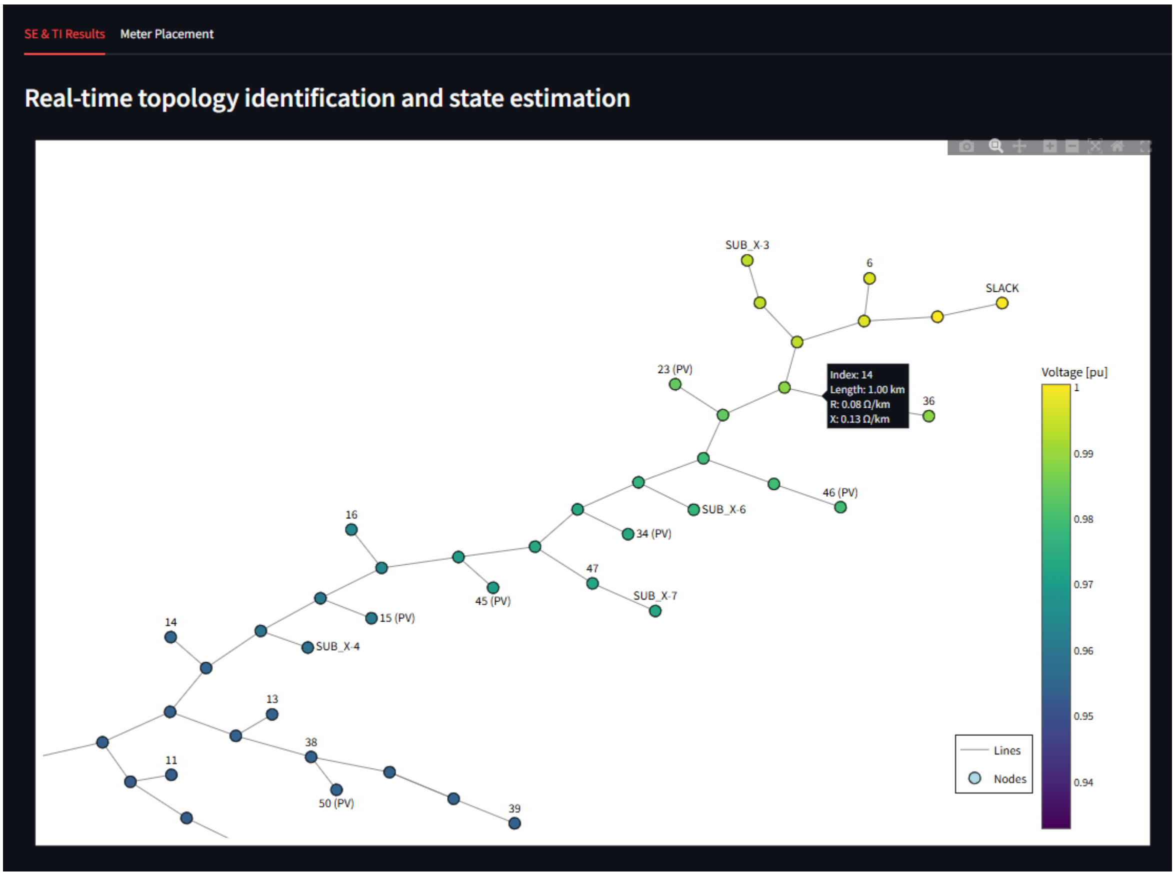


Figure 23: Line model details available via on-hover tooltip

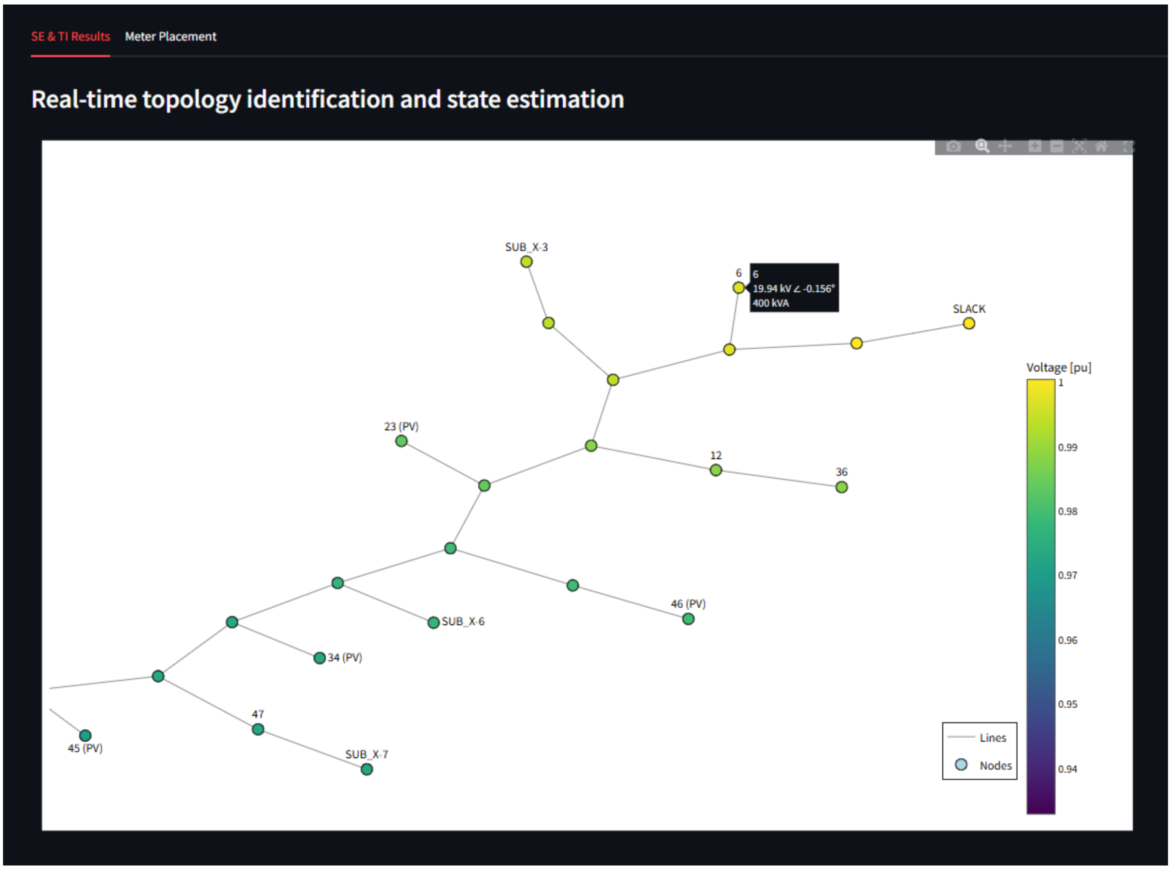


Figure 24: Detailed state estimation results available via on-hover tooltip

Extra functionalities of the SE module include: 1) Derivative information on active and reactive line power flows, displayed via on-hover tooltips for each line, computed by applying power flow analysis to the SE outputs, 2) real-time alerts for detected voltage violations and line congestions, and 3) a dedicated tab presenting graphical visualizations of SE results, either in real time or based on historical data, enabling users to track trends in the network voltage profile. These additional features will be activated following the on-site installation of PMU devices by HEDNO.

The "Meter Placement" UI Tab provides information pertaining to the proposed meter placement scheme, and is shown in Figure 25. This Tab also uses *plotly* to render a graph-based network layout that overlays candidate PMU locations and existing Advanced Monitoring Device (AMD) sites. On the network graph, optimal locations (nodes) for PMU installations are colored in red, while nodes with pre-existing meters are colored in yellow. The UI can be updated to reflect newly generated results following user-driven re-execution of the ML-based optimal meter placement algorithm (see Annex 7.2 for a detailed description of the developed methodology) with new inputs and configurations (different meter types, grid changes etc.).

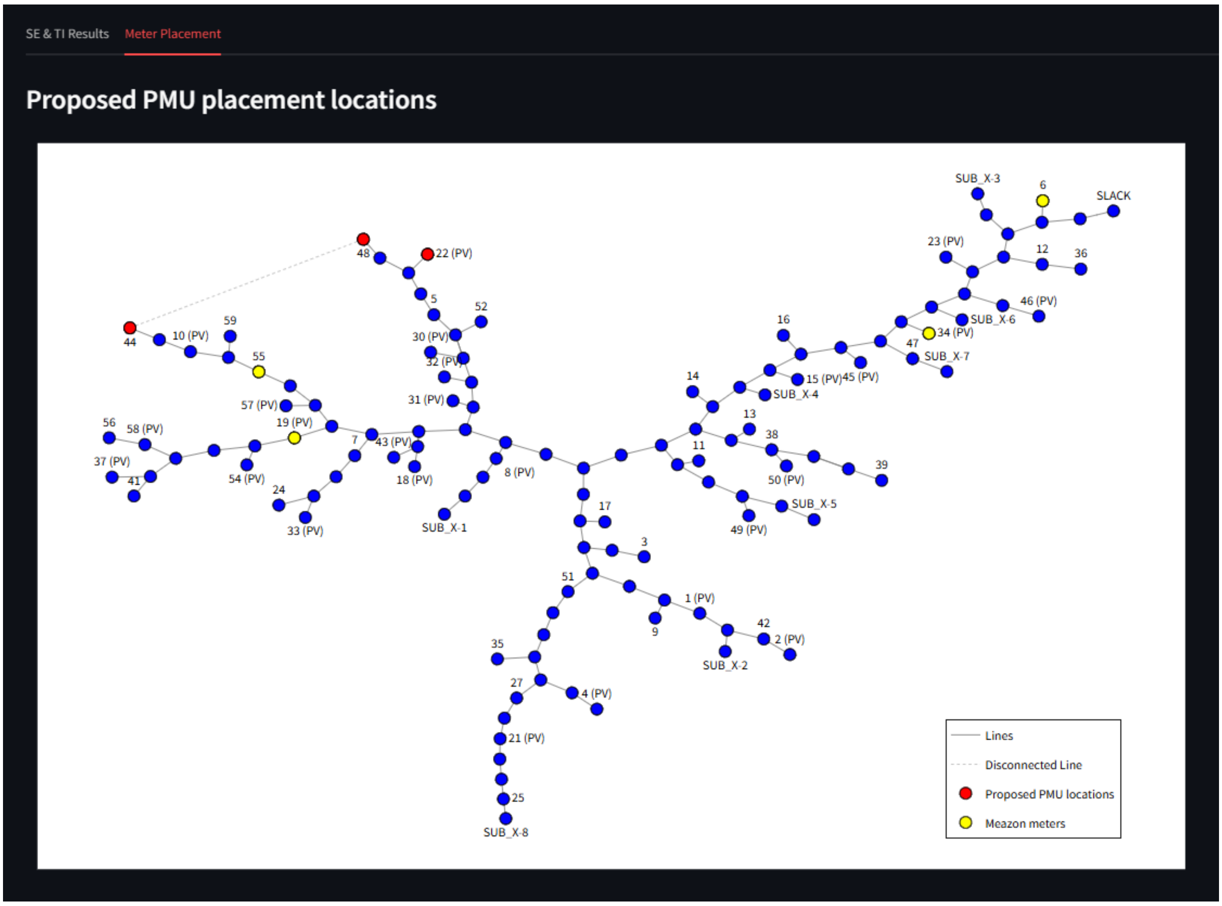


Figure 25: Indicative results of the meter placement design task

Finally, it is also useful to note that users can switch seamlessly between the two UI Tabs, without interrupting the automatic refresh of the "SE & TI Results" Tab, which continues to be updated at the specified intervals. Furthermore, if the estimated network operating conditions –e.g., the current network topology– remain unchanged between successive DNN output updates, then the UI caches and reuses the related graphical objects (in this case, the network graph topology) instead of drawing them from scratch, thereby conserving significant computational resources.

4.4 Topology detection tool

4.4.1 Description

Distribution system operators (DSO) operate and control the medium and low voltage networks. For them, understanding the topological structure of a power grid and laws of changes within it in a timely manner based on measurements is of paramount importance: it is required to have reliable information about the network topology and up to date measurements of electrical parameters. This situational awareness is normally more developed in the medium voltage (MV) side than in the low voltage (LV) side, but in both cases, it is far from being perfect, due to the limited placement of real-time metering devices. This is in stark contrast to high voltage (HV) transmission systems that usually enjoy full observability and breaker/switcher statuses on lines are reported in real-time or identified jointly while estimating system states via the generalized power system state estimators.

The biggest problem are the LV lines (also known as feeders). Here the lack of measurements, due to the lack of sensors or an appropriate communication channel makes almost impossible to have a reliable network monitoring system: There may be thousands of buses in a distribution system where only a hundred of them are monitored with real-time measurements. This scarcity of sensors is linked to the fact that LV networks are huge and contain several connections, that are (economically) impossible to monitor in real time.

The observability problem is partially alleviated in OPENTUNITY with the use of the **enhanced state estimation** system described in section "4.2-Enhanced state estimation tool", that aims to retrieve the unknown system state, that is, the complex voltages at all buses and connection points so that the gap of missing real time measurements in filled. However, the state estimation greatly depends on the grid topology, but this might contain inaccuracies for different reasons:

- The LV network may be affected by public works and incidents that might end up with not logged-in changes in the topology, made on a rush to restore service for customers.
- LV network topology changes frequently due to normal power engineering activities aiming at reducing line losses, handling outages or accepting more intermittent distribution generators, but these operations might not be properly logged-in the topology database.
- LV Breakers and protections do not normally report status in real time, so the topology might have automatically changed as a result of a critical event without the DSO noticing.

The next diagram depicts where the error detection mechanism lies within the enhanced state estimation calculation process. The main difference with real time state estimation is that it is based on historical records and thus cannot work in real time.

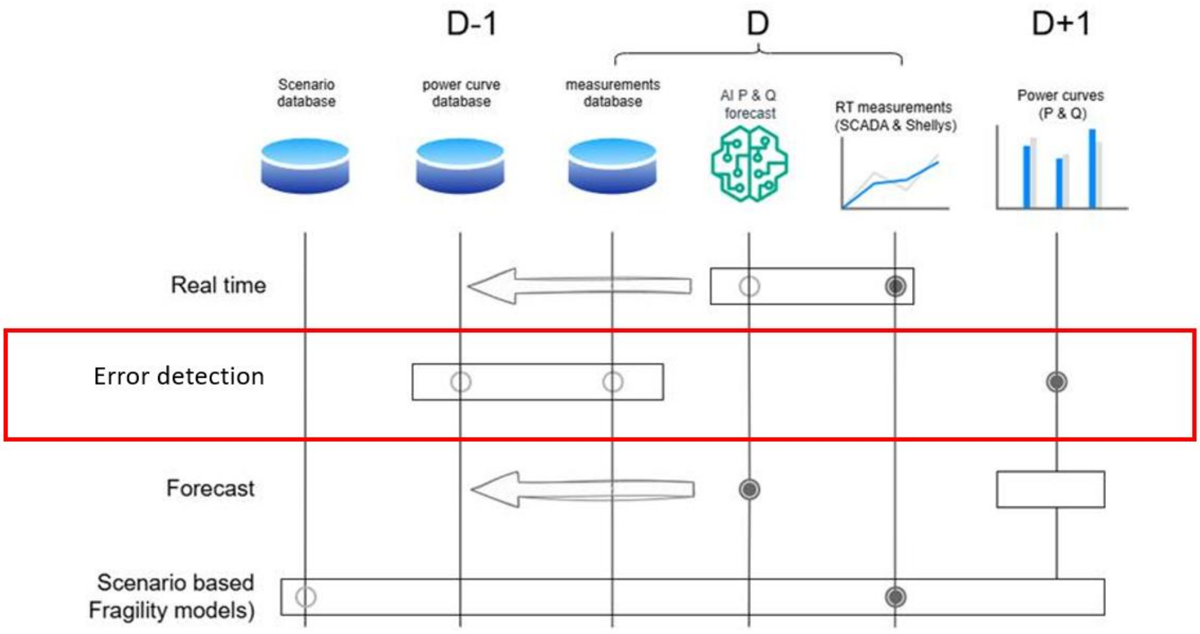


Figure 26: Topology error detection within state estimation process

In OPENTUNITY, there will be three different tools oriented to solve or alleviate for such problems and improve the situational awareness:

- The **topology detection tool** will try to identify the inaccuracies on the topological models of the utility by analysing the data received from the available network sensors and checking its compatibility with the stored topology.
- The **fuse burn detection tool for early outage and islanding recovery tool** will focus on identifying burn fuses on specific phases that might impact the quality of supply and even end up in islanding problems in specific areas. This process is described in section "4.5 – Fuse burn detection tool for early outage and islanding recovery", but the process is very sensible to inaccuracies on topological assignation of phases to customers. This detection of errors in phase-assignation is part of this topological detection functionality.
- **Non-Technical Losses (NTL)** is any electrical energy consumed and not invoiced and can therefore be considered fraud or energy theft. This can be considered a type of topological inaccuracy detection as it tries to identify loads not existing in the topology or under-measured

The process of detecting errors in the topology is based on the comparison of the real grid devices measurements received with the theorical measurements calculated according to the 'allegedly' real topology. In case discrepancies are detected that can't be explained by measurement errors or physical reasons (technical losses), the system will try to identify the most likely error in the topology.

The process for this detection is as follows:

1. The power curves of the smart meters will eventually reach the system through the AMI system.
2. The values of power curves are assumed as the values for P and Q of the supply points; no estimation is used but the real measurements.
3. Optimal power flow is calculated to obtain V, I and angles on the buses

4. In order for the topology detection to work, other electrical measurements apart from those coming from smart meters must be available, like SCADA measurements, test cycle values, or data coming from home metering (Shellys). If they are not or are insufficient, the process cannot continue.
5. The estimation of the state will try to balance the measurements following certain rules in order to obtain physically viable power flow results. These rules, in summary, will assign variability thresholds to each of the measurements used as inputs for the state estimation process. In this case, where the state estimation is based on historical data, the measurements for P & Q are more accurate than those used and described in the real time state estimation, where they are obtained based on ML models, so the variability thresholds are smaller:
   i) Smart meter energy values for P & Q will have a mid-level potential variability.
   ii) Calculated values V and I will have a mid-level potential variability bigger than the previous.
   iii) Data from SCADA, test cycles or shelly metering will have a very small variability.
6. State estimation is calculated with the following algorithm
   i) Power flow is calculated using P & Q measurements.
   ii) If it converges, power flow results (V & I) are compared to 'real' V and I measurements.
   iii) If there is a mismatch on the results, P, Q, V and I values are modified according to its variability. The process goes back to step I).
   iv) The process repeats until the estimated P & Q measurements are compatible with the real-time obtained measurements.
7. After state is estimated different results can be extracted:
   i) The variation of P applied to supply points is analysed. In case it is detected that a huge variation of P has been applied for the state estimation to converge, it is assumed that some consumption is missing in the network (NTL), and thus an alarm is triggered associated to the affected area. This is described in section 4.3 of deliverable OPENTUNITY power flow developments (v2).
   ii) The state estimation is not feasible with the given inputs, meaning that the real results are not compatible with the topology. In this case, the process starts calculating state estimation variants using alternative topologies by simulating changings in the configuration of the switches. This switch reconfiguration might imply the de-energization of some areas. If a given variant topology results in a more accurate state estimation result, the potential topology error is logged, and the operator is warned of a possible outage if needed.

4.4.2 User's Manual and Interface.

The topology detection tool core works periodically in an automatic way. The analysis described in the previous sections are performed and the OPENTUNITY ETER tool user interface is used to present operator the results of this analysis**.** This section will focus on the identification of incorrect information of switches, as the NTL is described in section 4.3 of deliverable D5.4 - OPENTUNITY power flow developments (v2).

The section where this information is presented is the topological grid section. In this section, when a switch is selected and the topological error detection detected a potential error in the status of the switch, this information is presented to the user:

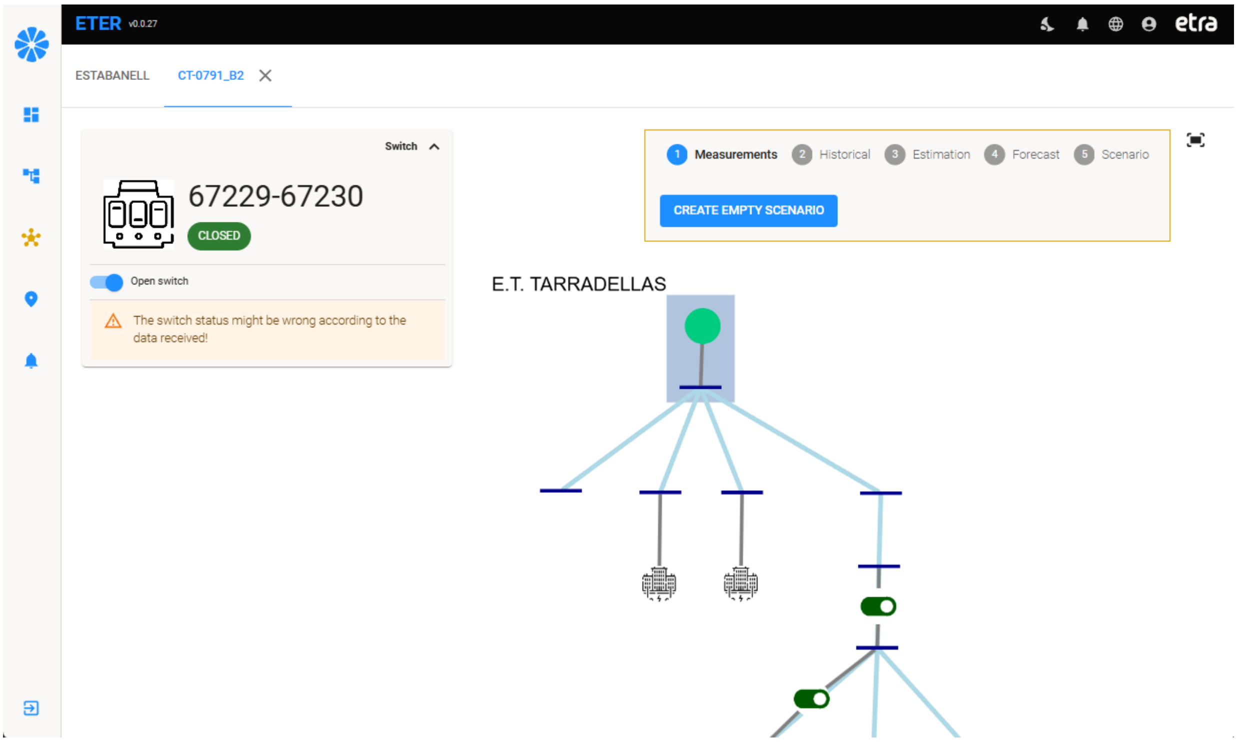


Figure 27: Switch with possible burned fuse

4.5 Fuse burn detection tool for early outage and islanding recovery

4.5.1 Description

A fuse in low-voltage (LV) networks is a protective device designed to safeguard electrical circuits from overcurrent conditions, such as short circuits or overloads. It consists of a metal wire or strip that melts when the current flowing through it exceeds a predetermined level, thereby interrupting the circuit and preventing damage to the electrical system or connected equipment. Fuses are commonly used in residential, commercial, and industrial settings to protect wiring, appliances, and other electrical components from potential hazards caused by excessive current.

Detecting a blown fuse in a low-voltage (LV) three phase power grid, particularly in a complex environment like a multi-apartment building, presents a multifaceted challenge. When a fuse blows, it disrupts the electrical continuity in one of the phases, potentially causing an imbalance in the system. This can lead to partial power outages, malfunctioning equipment, and even safety hazards.

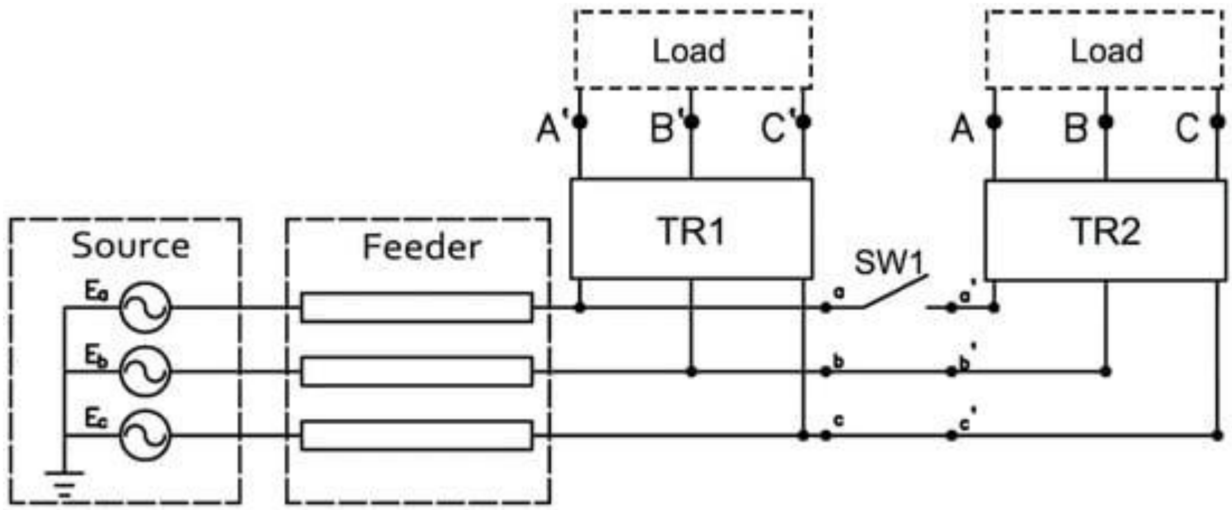


Figure 28: Connection of loads to individual phases in LV

Islanding occurs when a portion of the electrical grid, typically containing distributed energy resources (DER) like solar panels, continues to be energized and operate independently despite being disconnected from the main utility grid. This situation can pose safety hazards to utility workers, cause damage to equipment, and disrupt the proper functioning of the grid. Anti-islanding protection mechanisms are essential to detect and prevent islanding, ensuring that DERs shut down or disconnect when the main grid power is lost. This is the schema of the connection of a simple domestic PV system:

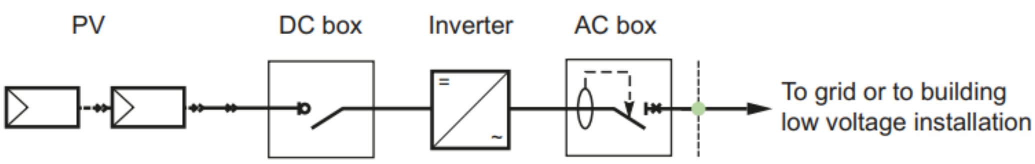


Figure 29: PV connection scheme in domestic environments

PV are arranged in arrays and producing DC current. This goes through an inverter that transforms the electricity to AC and connects to the LV grid. The PV systems always feature protection mechanisms that prevents islanding; however, these mechanisms are primarily designed to detect a complete loss of grid power. When only one phase is curtailed, detection can be more complex, and it could happen that the PV energy dangerously feeds a client connected to the curtailed phase:

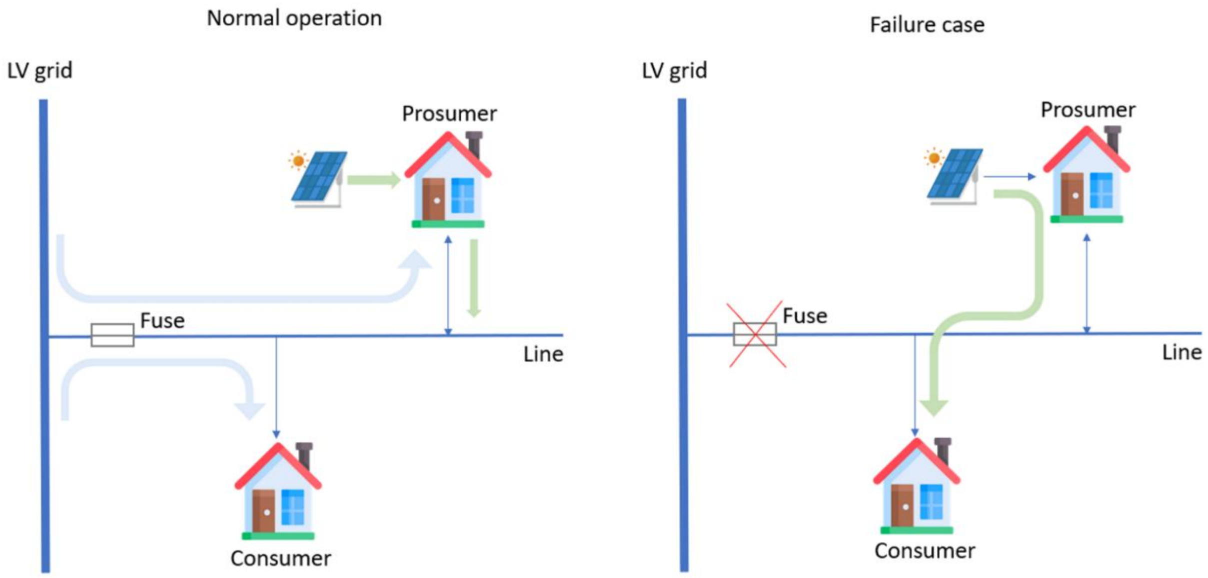


Figure 30: Example of islanding caused by blown fuse

The blown of a fuse should be considered not only as a disturbance of the customers' supply, but also as a security issue due to this potential islanding problem that might endanger user's infrastructure and pose a physical security threat. Therefore, it is of paramount importance to **detect blown fuses and pinpoint its exact location and phase through the monitoring of the voltage at end user level in a timely manner**. This is especially important when it occurs in remote or less accessible parts of the LV network. Traditional methods of detection, such as manual inspection, are time-consuming and impractical for large-scale or critical applications.

The triggering of the process is the awareness of an outage in a certain area of the grid. This detection can be done automatically with the measurements received by the different DSO control systems, or by the reception of phone calls from any of the affected customers.

The mechanism proposed make use of the capability of the system to periodically interrogate smart meters for obtaining close to real time measurements of them. Ideally, having all the P, Q, V, I and angle measurements per phase will allow to pinpoint the burned fuse location. Nevertheless, the nature of the PLC communication makes this process infeasible for large networks, as the interrogation must be done one-by-one, and every smart meter take some time to answer. To solve this, a mechanism has been defined to determine the exact location of the fuse burned in the minimal amount of time. The schema of the process is as follows:

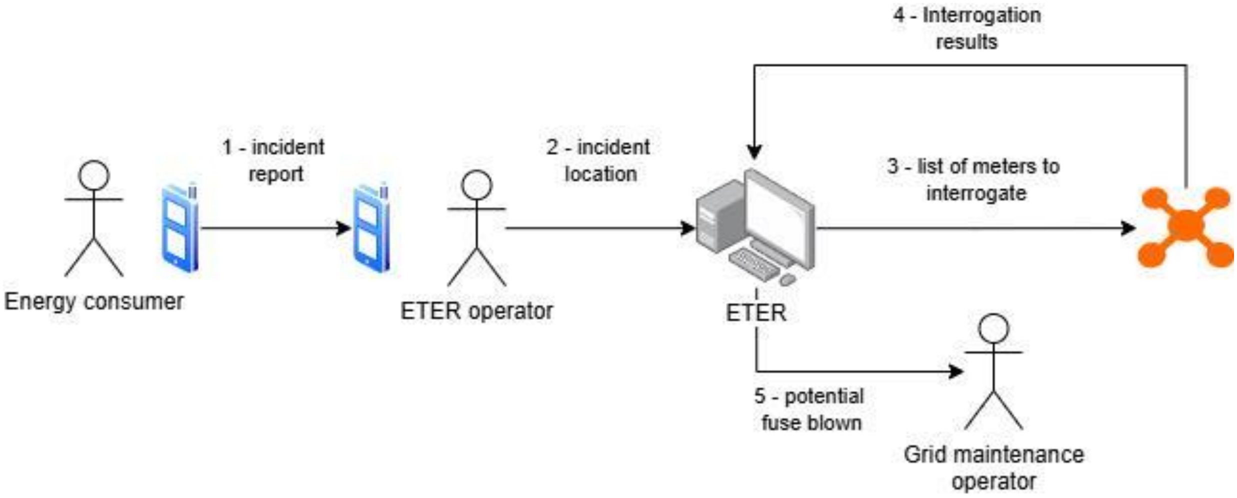


Figure 31: Fuse burn detection process

1) As described, the process starts with the identification of an outage in a certain energy consumer supply point. This outage might potentially affect a broader area, so instead of waiting for new complaining phone calls to arrive from other customers, the system starts a process to automatically identify the affected area and send the operators to fix the problem as soon as possible and with the most accurate information available.
2) The identification of the initially affected supply point is done in the ETER tool user interface, and this triggers a mechanism that calculates the list of smart meters to interrogate. This calculation is done by a process that takes as inputs the following information:
   a) The list of smart meters in the LV grid, with its phase connectivity information
   b) The list and location of fuses in the topology
3) The calculation involves the following steps:
   a) The possible paths upstream to the transformer/substation are determined
   b) The supply points/meters downstream of relevant fuses (per phase) are determined
   c) Based on the area/phase, identify all fuses that, if blown, could explain the observed outage pattern.
      i) For a single-phase outage: restrict search to fuses protecting that phase
      ii) For a zone: restrict to fuses upstream of the affected area but downstream of other unaffected supplies
   d) For each candidate fuse, determine the set of customer meters supplied through it on the suspected phase.
   e) For each candidate fuse, **select a representative subset of downstream meters**:
      i) Ideally meters are close to the fuse or optimally at branch points to best discriminate between candidate faults
   f) Prefer meters supplying only the affected phase(s).
      i) If two candidate fuses have non-overlapping downstream customers, query one from each
      ii) If branching, querying a meter right after a fuse lets you know if everything downstream is likely affected
3) The meters to query are then passed to the DSO systems to perform real interrogation on them. If there is no direct configuration of the interrogation system (test cycles), the information is presented in the ETER tool interface for manual configuration

4) After a while, measurements from selected smart meters will arrive. Using them the system will deduce the blown fuse/fault location:
   a) If only meters downstream of a certain fuse are out, isolate that fuse.
   b) If all meters past a branch are okay, eliminate that path/fuse.
5) The results will be presented ETER for the DSO to send operators to fix the problem in a timely manner.

4.5.1 User's Manual and Interface.

The fuse burn detection tool is triggered by the reception of an outage report and the introduction of the details in the OPENTUNITY ETER tool user interface: This is done by locating the supply point with the issue in the topology view and clicking the appropriate button:

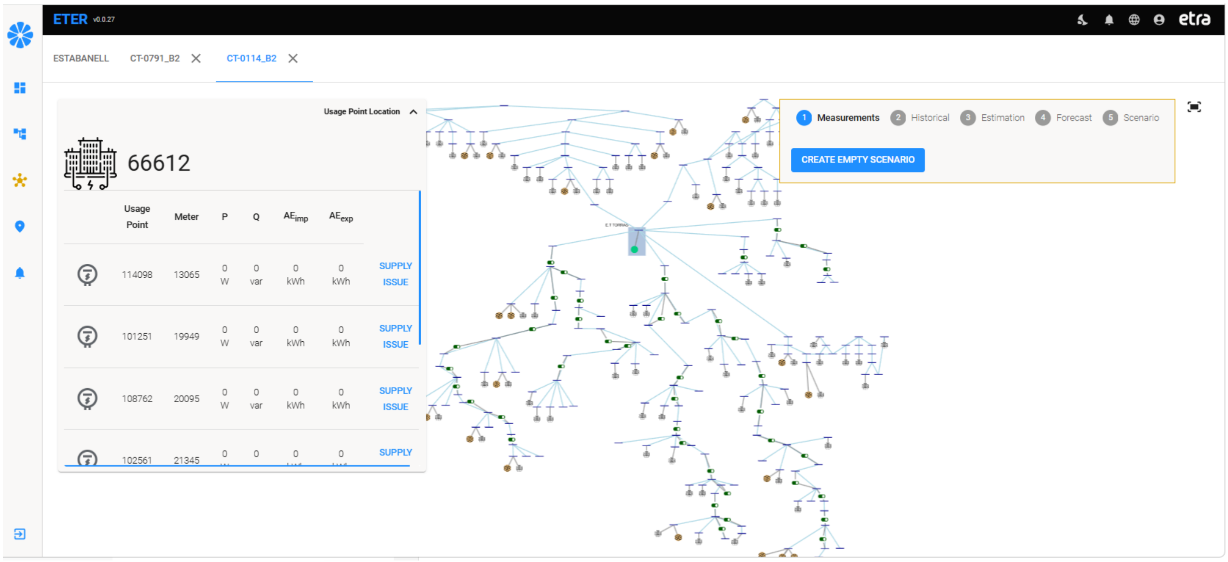


Figure 32: Identification of an outage meter in the ETER interface

Clicking on "supply issue" will trigger the process and present user the list of meters to interrogate using the process described above:

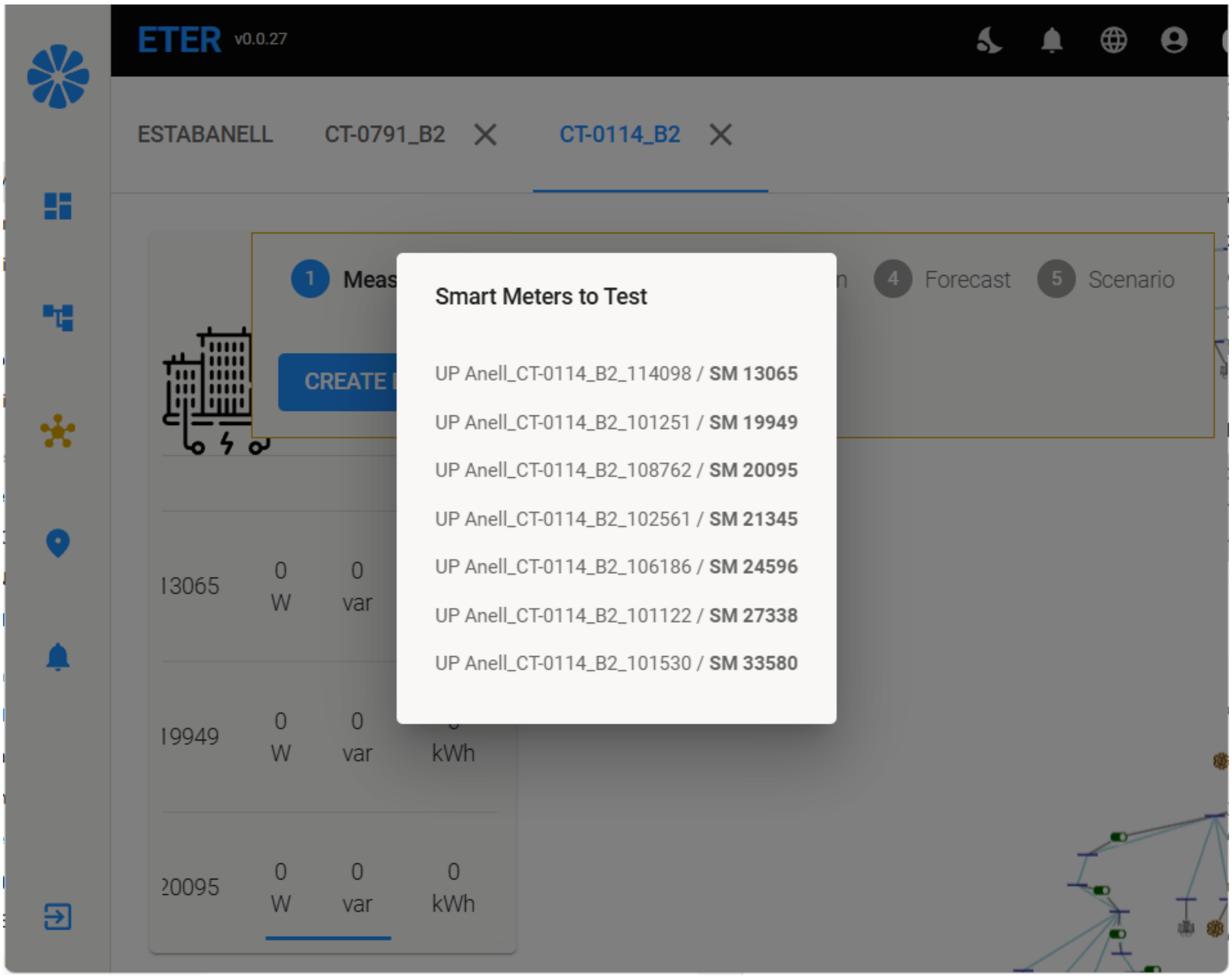


Figure 33: List of smart meters to test

This list will be configured by the DSO using its control system for this. In the case of the Spanish Pilot, this involved uploading a file with this information to an FTP of the MV/LV substation of this grid.

Eventually, the measurements will arrive to the system and system will determine the potential location of the burn fuse. This process can last up to some minutes, depending on the status of the network and the meters affected

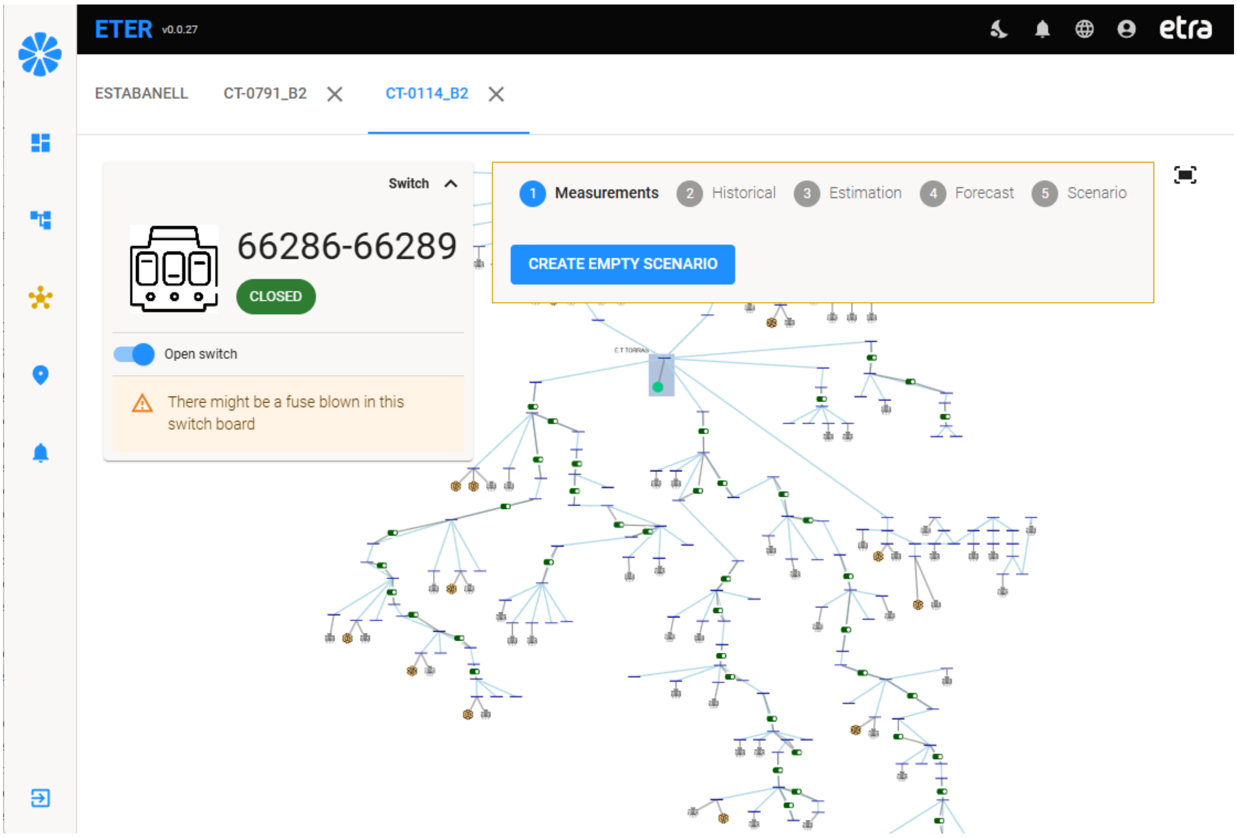


Figure 34: Burned fuse detected in the topology

4.6 Critical point detection tool

4.6.1 Description

DSO's LV networks have usually a radial structure from the secondary bus of the electrical transformer. The infrastructure used for supplying electricity to all clients is composed by several small cable segments that are deployed following the structures of cities and towns towards the different connection points. This is an example of how the feeder span from the MV/LV substation to reach all clients in dense populations.

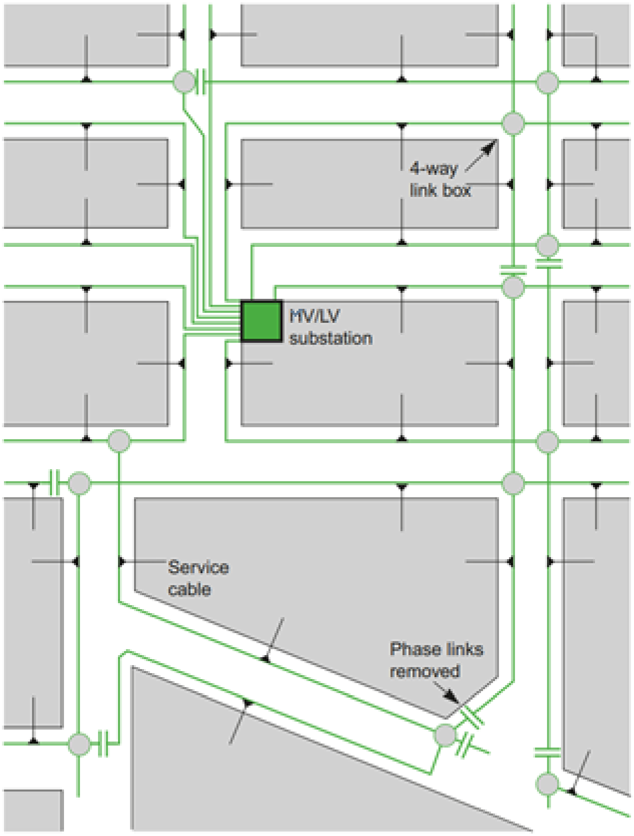


Figure 35: One of several ways in which a LV distribution network may be arranged

These cables could have different characteristics: section size, composition, insulation, aerial or subterranean, etc. These characteristics determine the maximum capacity of the network and must be carefully considered to allow for new electrical connections.

One problem linked to this is the fact that since the cable section gets smaller as it goes further away from the transformer and the penetration of PV and EV is normally higher, there's a potential risk of **congestion** in parts of the line with lower sections of cable. Also, the **voltage drop** could be a problem in the sections of the network far away from the primary bus.

The LV cable infrastructure also determines the protection devices required. These devices are essential for ensuring the safety, reliability, and efficiency of electrical systems. These devices, including circuit breakers, fuses, Residual Current Devices (RCDs), and Surge Protection Devices (SPDs), are strategically installed to safeguard against various electrical faults such as overcurrent, short circuits, earth faults, and voltage surges. Circuit breakers and fuses protect wiring and equipment from damage caused by excessive current, preventing potential fire hazards and equipment failure.

Protection devices in Low Voltage (LV) networks are selected and configured using **short circuit current calculations**. These calculations determine the magnitude of fault currents that can occur during a short circuit, which is crucial for selecting and setting protection devices. The calculation results are used for:

1. **Protecting device selection:** Short circuit current calculations help in choosing appropriate protection devices (circuit breakers, fuses, RCDs) that can manage and interrupt the maximum fault current without damage.

2. **Setting trip parameters:** The calculated short circuit currents inform the settings for trip thresholds and response times of protection devices, ensuring they operate correctly during faults.

Distributed Energy Resources (DERs) connected to distribution systems affects the fault current and power flow direction. The most significant impact of DERs on distribution systems relates to increasing the short-circuit current and contributing to the fault current for downstream faults. As a result of the fault current increase in distribution networks, DERs units might reduce the contribution of the system's fault current which in turn causes the protection system to be blinded and cause malfunctioning of protection systems during faults. For instance, if a fault occurs at one of the feeders adjacent to DG units, an undesired tripping command by protection relays may be triggered. As such, it should be noted that the location of DERs in distribution systems (as well as their number and penetration level), highly impacts protection systems.

The aim of this tool is to evaluate the sections of the LV network that are prone to errors (or in other words more fragile or critical) given the current network topology and considering different power flow scenarios, like peak load, PV generation surplus, line tripping, fuse burn, etc. The tool will allow to define such scenarios and will make the required calculations to identify the following problems:

- **Congestion in cable sections**. Each cable has an inherent ampacity and over currents (congestions) could happen if the network is not properly structured and dimensioned.
- **Voltage problems**. The voltage profile at the LV network buses could be affected by the location of DERs.
- **Incorrect protection settings**. The short circuit current could be affected by the presence of DERs in the LV. The short circuit current will be calculated for all LV buses in the selected scenario and compared to the nominal characteristics of the protection systems. The simulation could help identify situations where the protection scheme is not appropriate.

4.6.2 User's Manual and Interface.

The OPENTUNITY ETER tool user interface allows evaluation of different scenarios for assessing the behavior of the grid when facing extreme situations. The concept of *scenario* is introduced here and can be defined as a snapshot of a grid in a given moment. Scenarios can be defined in different parts of the ETER tool:

- When the Measurements visualization is selected, the tools allow to create an empty scenario.

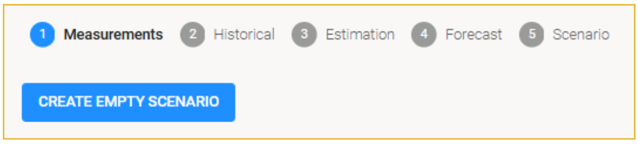


Figure 36: Button for create empty scenario

- When the historical, estimation or forecast visualization is selected, the tool allows creating scenarios based on the selected grid estate.

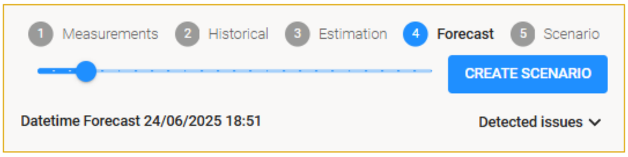


Figure 37: Button for create scenario based on existing grid state

When the button is clicked, the user is prompted with a dialog for defining scenario name:

Figure 38: Scenario name definition dialog

Regardless of the mechanism used for defining the scenario, the scenario is added to the list of available scenarios for the current grid, with the current topology and current measurements for load, supply points and generators.

The list of scenarios for the current grid can be found in the 'scenario' visualization mode:

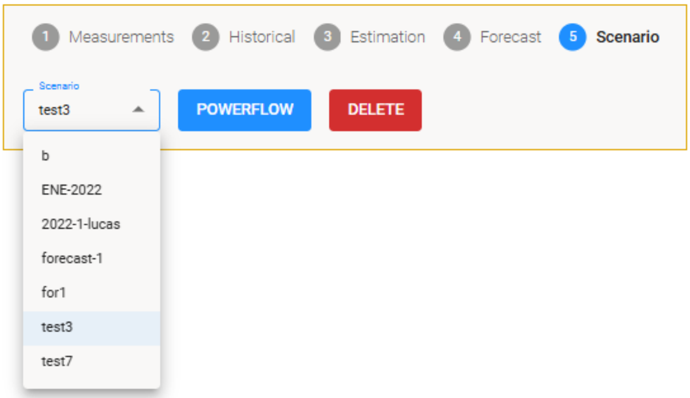


Figure 39: Selection of scenario

By selecting the scenario, the values associated are recovered and shown in the topology viewer:

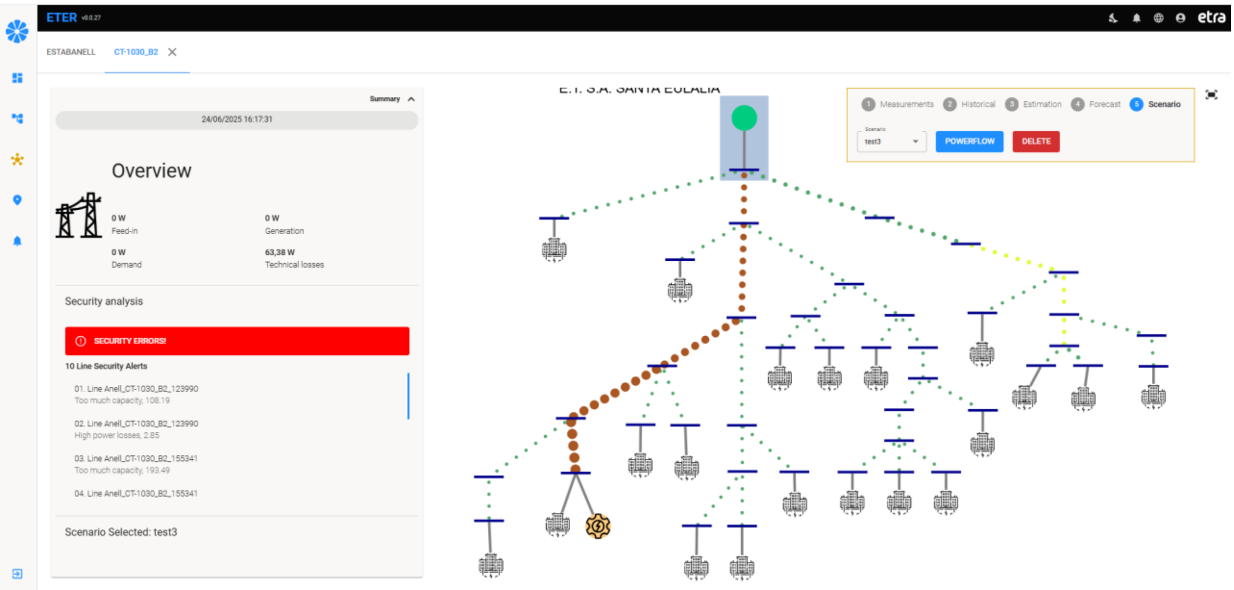


Figure 40: scenario results show in the topology viewer

In case the power flow has been calculated, the lines are drawn according to these results, and the overview section presents the results of the steady state security analysis of the power flow calculated. In the example above, there are different congestions in some lines, and the list of errors is presented as a list in the overview section

The measurements of the element in the selected scenario are shown when clicking on them in the topology:

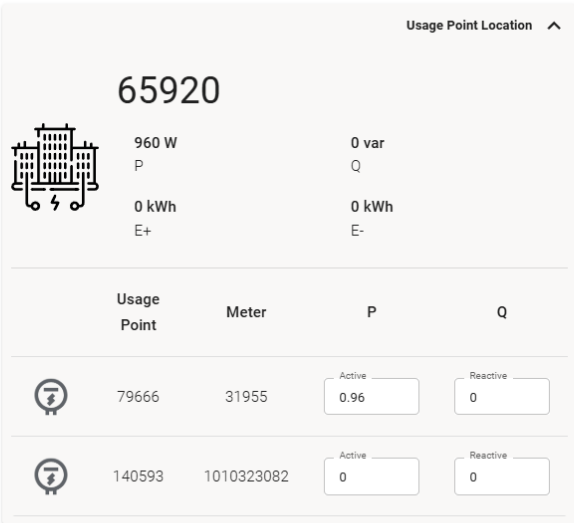


Figure 41: Usage point location details in scenario

The information presented is the same as these presented in other visualization models, except that the values for active and reactive power can be modified. In the picture above the details of a usage point location is shown, and the linked supply points values for active and reactive power can be modified individually.

Other scenario elements that can be changed are distributed generators and switches:

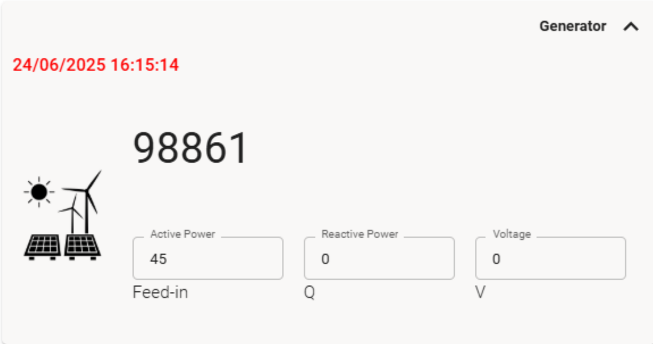


Figure 42: Details of distribution generator in scenario

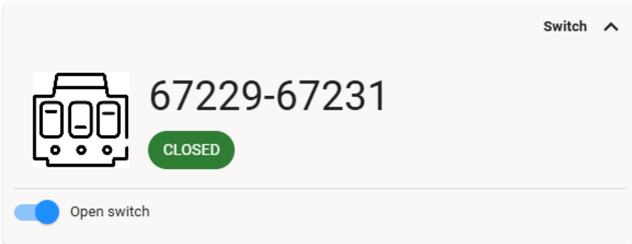


Figure 43: Details of switch in the scenario

Changing the active and reactive power values in the scenario elements for will automatically add these new values to a list of changes to apply. Changing the status of the switches (opening or closing) has the same effect. In the overall grid view, the list of changes to apply is presented at the bottom, including the new values for the selected topology elements:

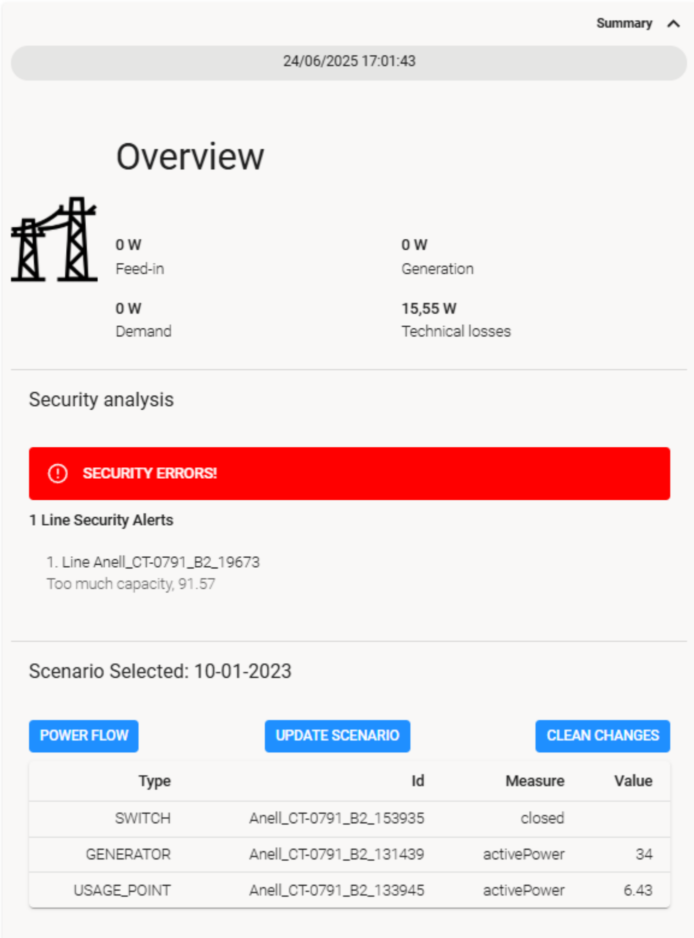


Figure 44: Scenario with changes to apply

When all the required changes have been added, the user can select the option for running a power flow with the new values. This will apply the changes and calculate the resulting power flow, presenting the results I the topology and the errors in the security section.

The other option the user can select with the changes is to store the changes in the scenario database, so that the scenario will now include such values. Finally, the changes can be removed in case they are not needed anymore.

This scenario topology creation and modification can be used to test and detect critical points in the topology. To do so, the operator can create a scenario from a period of time where the grid is particularly stressed like during winter or summer consumption peaks. Then, active and reactive power can be manually changed in the topology to reach levels that are not normally seen (like maximum generation or abnormally high consumption). The calculation of the power flow on these extreme scenarios will provide information about the critical points of the network, like bottlenecks or crowded feeder with voltage problems. These results will be presented in the overview of the scenario after running the power flow.

4.7 Short term analysis of the impact of DER in the Distribution grid

4.7.1 Description

Distributed energy generation (DERs) has been introduced to power systems, particularly at the Low Voltage level, to make the existing systems more reliable, secure, and efficient. Simultaneously, DER brings different challenges to the system as existing systems are not yet ready to accommodate high DER penetration levels. In this respect. since the current and future trend of electric power systems is set towards increased integration of DERs, a discussion of the impacts of those generation technologies on distribution networks is needed.

Due to the relatively small size of DERs and the policies of DSO that restrict location and dimensioning of DERs to prevent capacity problems, usually, there are no congestions problems linked to the installation of DERs. Nevertheless, there are two types of problems that DSO may face when DERs are deployed at the LV networks, **capacity** problems and **voltage** problems.

Capacity problems are related to the dimensioning of the networks. Low voltage networks are designed to distribute sufficient energy to all customers. To manage uncertainties in load consumption, each supply point is capped with a maximum active power limit. If consumption exceeds this limit, the customer experiences curtailment. The dimensioning of the network considers the sum of the limits of all the customers in a feeder.

The *simultaneity factor* is a coefficient used in electrical engineering to estimate the peak load on a distribution network. It reflects the probability that multiple consumers will not use their maximum active power demand at the same time. By applying this factor, DSOs can design more efficient and cost-effective low voltage networks, ensuring adequate capacity without over-dimensioning. This factor typically ranges from 0.6 to 0.8, indicating that only 60-80% of the maximum possible load is considered for network planning by the DSO. This factor is legally regulated in all countries.

The simultaneity factor can be impacted by Distributed Energy Resources (DERs). DERs, such as solar panels and battery storage, can introduce variability and unpredictability into the grid. This can affect the traditional load patterns and potentially reduce the accuracy of the simultaneity factor, necessitating adjustments in network planning and dimensioning.

There are different approaches to tackle this issue, but we will focus on enhanced forecasting models that will identify problems in the network during peak distribution generation periods. The idea is to identify these problems beforehand by running state estimation techniques using short term DER generation forecasting (on PVs).

Whilst capacity problems can be observed in the power flows at steady estate, **voltage** problems normally affect the transient state while the system is not yet stabilized. Voltage problems can appear as a result of fast and simultaneous changes in active and reactive power injections of elements in the grid, and this is something that can happen in high DER penetration areas. In other words, the simultaneous and abrupt reduction of generation in several DERs in a certain grid area can produce oscillations and bring the voltages over the limits before the power flows rearrange and the LV is re-energized with energy flowing from MV. This is an example of transient behavior of a generator abruptly curtailing its power:

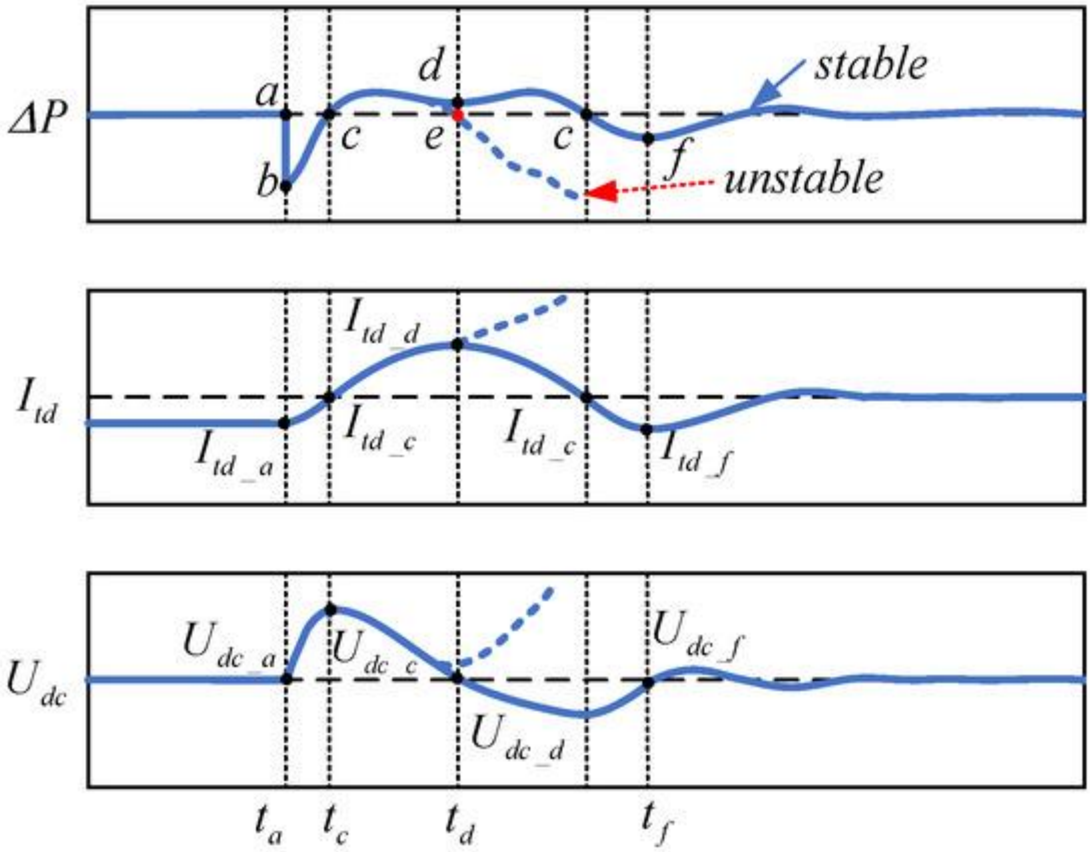


Figure 45: Example of transient behaviour.

Even though at the steady state all magnitudes stabilize at time t_f, the change on the active energy injected produces temporal oscillations in the current and the voltage at the supply point. This might lead to problems in nearby grid devices and could even produce outages if the energy curtailed in big enough.

Both types of security problems must be addressed beforehand, based on the demand and generation predictions.

The core of the **capacity problem detection** process is based on the calculation of power flows.

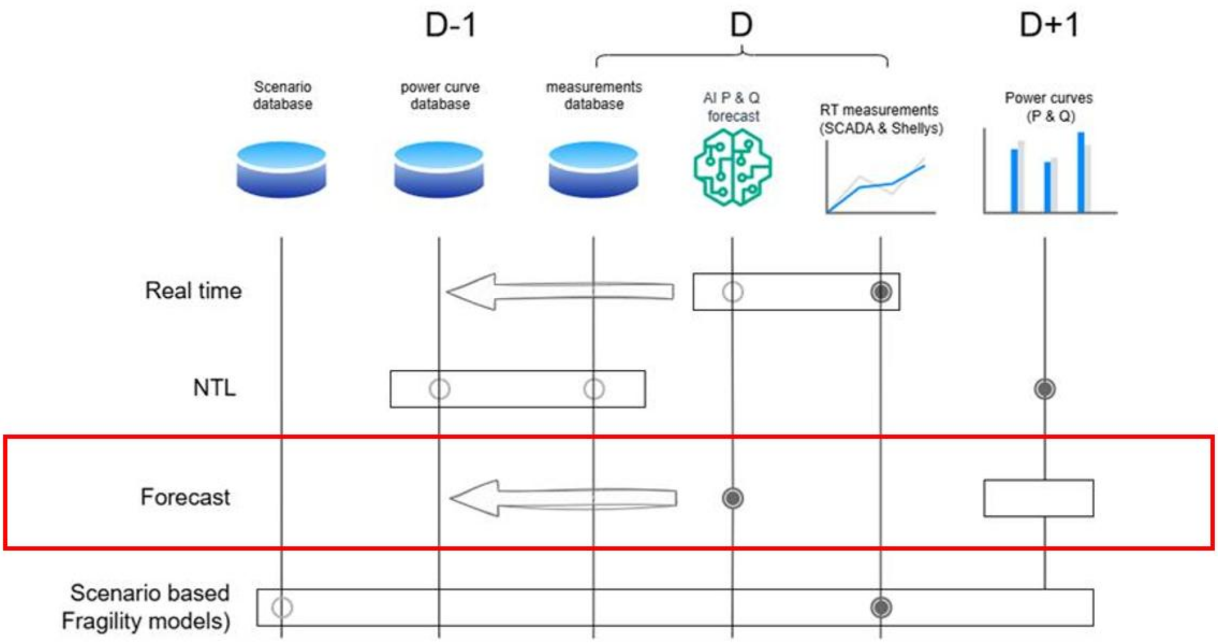


Figure 46: Time horizons

In this case, the demand and generation forecast are taken from ML models of the loads and DERs. The ML models are correlated with weather information (solar irradiation in this case), and the prediction calculation takes into account the forecasted weather for the area.

With these estimations, power flow will be calculated every hour for the next 24 hours. In case the steady state calculation detects congestions (capacity problems), the information is presented in the ETER tool for the operator to take the appropriate actions to solve the problem.

The **voltage problems detection** goes a step ahead of the steady state power flow calculation by making use of dynamic models for the elements in the grid. These models try to mimic the electrical behavior of the power electronics of the energy grid assets. The calculation process for detecting these problems follows these steps:

1- The DERs in the grid are identified and dynamic models are selected for them according to the DERs characteristics
2- A time series is generated covering a few numbers of seconds after the forecasted power flow. The time series granularity is 50 Hz (50 steps per second)
3- The time series will set up P and Q values for the element in the grid according to these rules:
   a. Loads will have constant P & Q values from the power forecast estimation.
   b. Generator will have a value of P and Q that will change through the time period, starting from the forecasted P & Q and abruptly dropping to zero injection. The actual values of P, Q, V and I will be extracted from the models simulating the behavior of the DER when energy is curtailed.
4- For every time step, a power flow will be run to identify potential oscillations that might create voltage problems.
5- The results will be identified in the ETER tool user interface.

4.7.1 User's Manual and Interface.

The short term analysis of the impact of DER in the distribution grid is calculated periodically in an automatic way. The analysis described in the previous sections is performed hourly and the OPENTUNITY ETER tool user interface is used to present operator the results of this analysis.

To access the results, the operator must select the forecast view in the topology section of the ETER tool. This view features a slider that allows selecting near-future periods of time (up to 24 hours ahead), and reviewing the results:

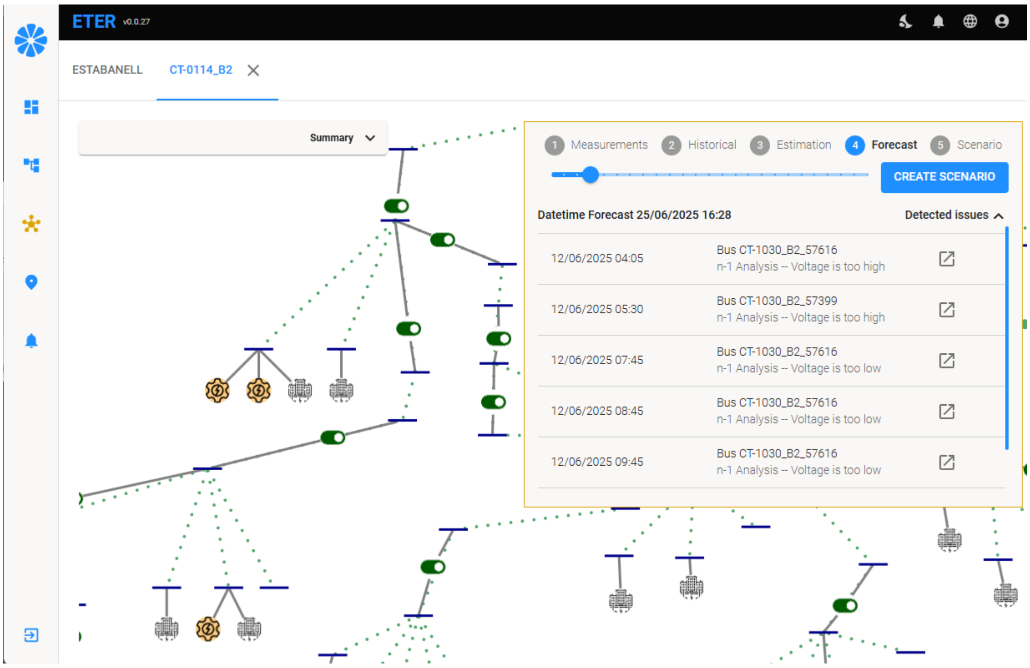


Figure 47: Power flow forecasting results

By selecting a future hour, the following results are presented:

- The **voltage problems** are shown in the forecast view section, under the "detected issues" title. This list identifies the buses that might present problems in case of heavy curtailments.
- The capacity problems are shown in the overview section of the grid:

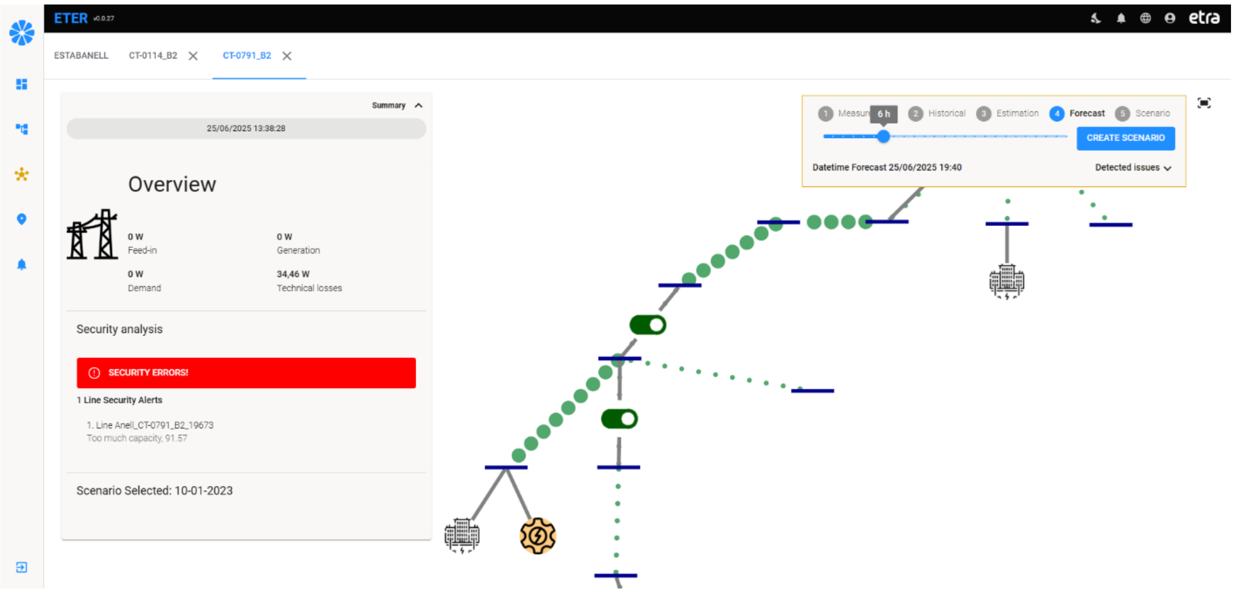


Figure 48: Capacity problems

In this case, the forecasted generation of the DER exceeds the capacity of the line.

4.8 Real-Time Thermal Rating Module

4.8.1 Description

Utilization of static limits for overhead lines by system operators usually lies on calculations based on the worst-case scenario for expected environmental conditions. On the other hand, Dynamic Line Rating (DLR) or RTTR systems lies in the calculation of the maximum current, that leads to the temperature limit in the overhead conductor. This method does not consider the worst-case conditions, but rather considers the existing environmental conditions, solar radiation, wind speed and direction and ambient temperature. In this respect, additional capacity can be unlocked in the transmission/distribution lines, the system flexibility can be increased, future investments decisions can be better informed by accurate knowledge on the actual line loading conditions and higher RES penetration levels can be achieved.

Direct methods to compute the RTTR for industrial practices, measure either conductor sag, conductor ground clearance, line tension or conductor temperature. Indirect methods for RTTR, analyze weather data at specific locations along a transmission line to calculate the current carrying capacity of the line. For both methods, measurements of current in the line are required, as well as weather measurements on different sections of the line, requiring multiple sensors along the line.

Moreover, RTTR applications are mainly linked with transmission lines, with limited research and industrial focus is noted on distribution feeders. It should be noted that a distribution feeder might have different current in various sections, unlike a transmission line that has the same current flowing in all its sections. In this respect, an industrial approach may require an increased number of sensors to measure the different current values among the feeder sections, while also gathering conductor temperature and weather measurements. Thus, a sensor based RTTR approach might not be cost effective

The RTTR approach in OPENTUNITY proposes a low-cost solution for distribution systems utilizes high-resolution weather forecasts to estimate conductor temperature. Moreover, it employs machine learning methodologies to forecast the current values based on existing measurements of the distribution network. Details on the methodology can be found in D5.1.

4.8.1 User's Manual and Interface.

In this section a detailed overview of the UI of the RTTR tool is presented, that can serve as a user manual.

Figure 49 illustrates the data flow architecture of the RTTR tool designed for real-time asset assessment and forecasting. The system begins with a sensor device that collects real-time operational data and transmits it to a central database via an API, with updates occurring at regular intervals (e.g., every 15 minutes or hourly). **This information from the sensors is collected solely for evaluation purposes.**

Users interact with the system through a dedicated User Interface (UI). Within the UI, users can view monitored assets (e.g., transmission lines), upload network topology files and historical data in a specified .csv format. These inputs—alongside data from other sources such as SCADA and the real-time sensor feed—are used to train machine learning models for forecasting.

Model training is performed on a scheduled basis (e.g., weekly) or triggered manually when new historical data is uploaded. The trained models generate predictive outputs, including real-time thermal ratings (RTTR), conductor temperatures, and current forecasts.

These results are made available to the user through the UI. Users can access historical logs by selecting specific time intervals or view real-time forecasts for up to six hours ahead, covering parameters such as line current, conductor temperature, and RTTR.

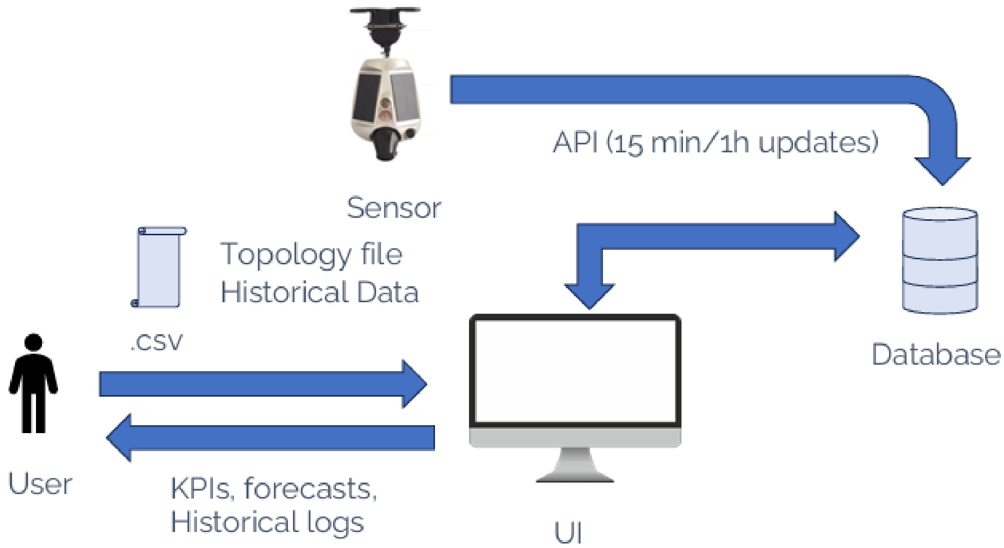


Figure 49: RTTR tool architecture

The UI has 4 different tabs: Home, Import Historical Logs, Historical Data Dashboard, Real Time Data dashboard.

The **Home** tab serves as the initial point of interaction for users within the monitoring tool. It displays the assets (lines) that have been registered. If no assets are currently registered, the interface notifies the user and advises them to contact the tool administrator to resolve the issue (Figure 50). When assets are present, the tool presents the list of registered lines. For each line, the system checks whether a topology file has been provided. If a topology has already been uploaded, the interface confirms its presence via a message (Figure 51).

Figure 50: RTTR tool home tab (no asset registered message).

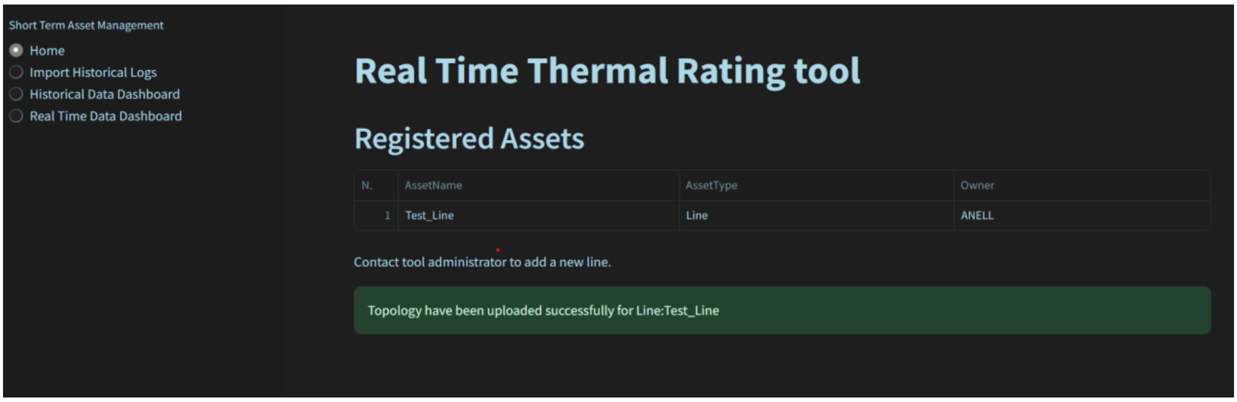


Figure 51: RTTR tool home tab (presentation of assets, success message for topology upload).

If the topology is missing, the user is prompted to upload the required topology file.

The user is requested to upload a topology file in .csv format (Figure 52). Upon upload, the system automatically checks the structure and format of the file to ensure it meets the required specifications. The user is then informed whether the file format is valid (Figure 53) or not (Figure 54). If the format is correct, the corresponding line is processed and visually presented on the map within the user interface (Figure 55). The map is interactive and the user can click on different line sections to view data, i.e. cross section, static rating, type of line (OH: overhead, UG: underground) and name of section.

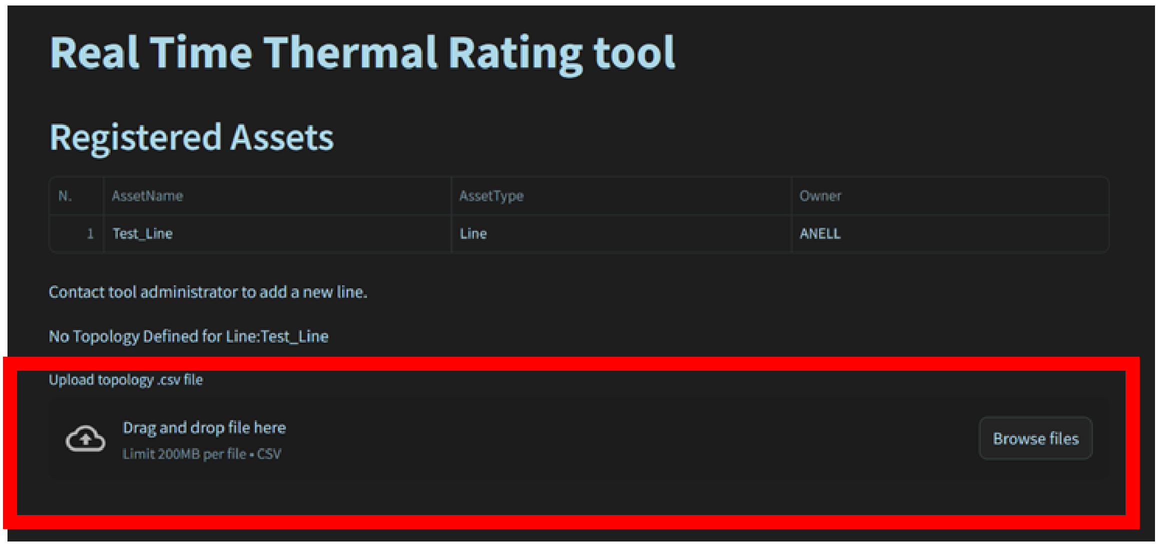


Figure 52: RTTR tool home tab (line topology upload).

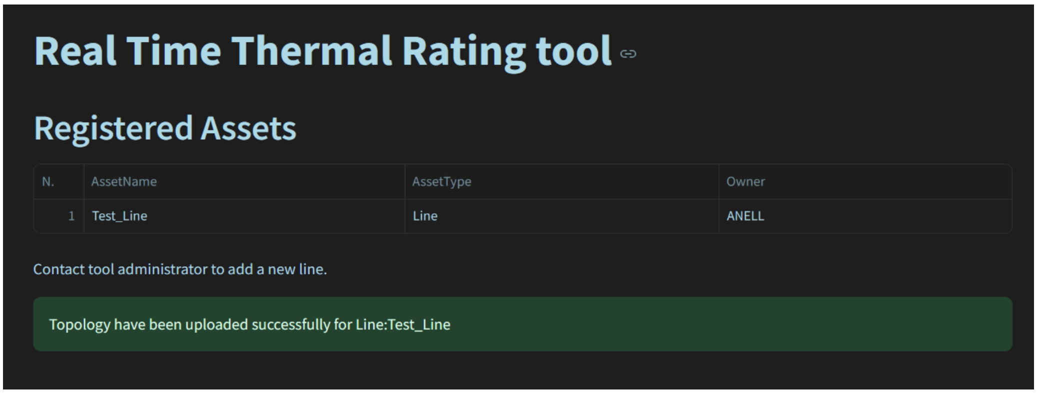


Figure 53: RTTR tool home tab (line topology upload success message).

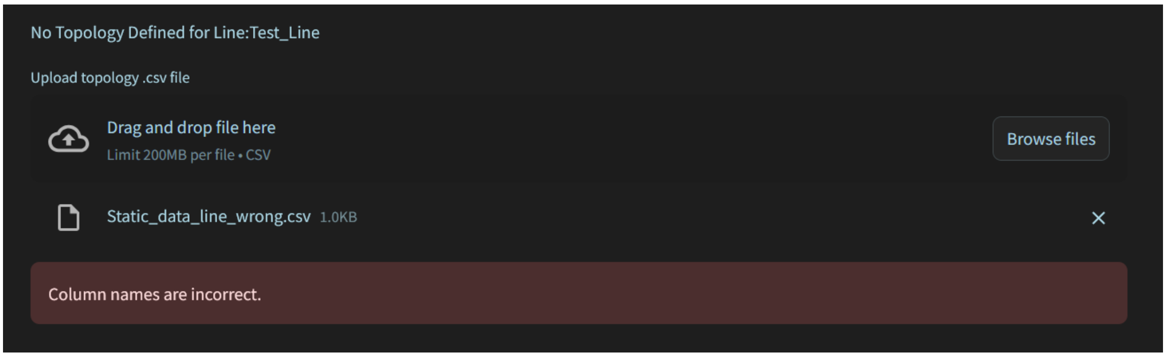


Figure 54: RTTR tool home tab (line topology upload error message).

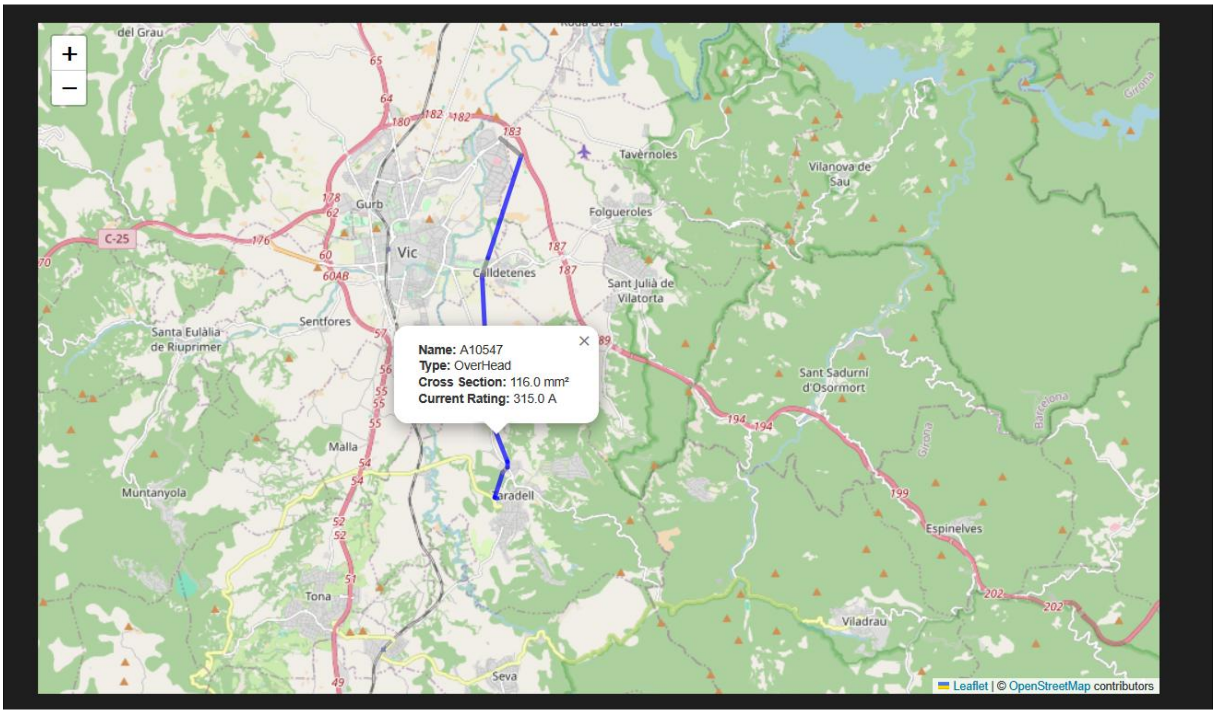
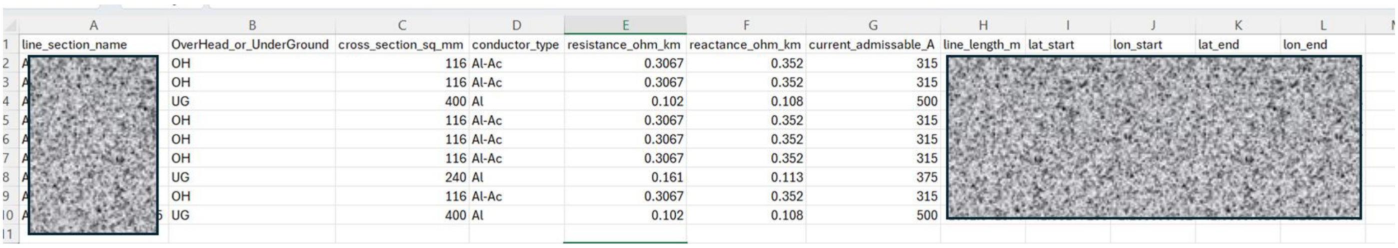


Figure 55: RTTR tool home tab (line topology map representation)

The line topology file must be provided in CSV format with UTF-8 encoding (Figure 56). Thus, the user has to make sure that the .csv file is saved in that format. The topology file is used to define the physical and electrical characteristics of each line section of the assets (lines) processed by the tool.

Each row in the file represents a single section of the line, with the following required fields in the specified order:

- *line_section_name (string):* A unique identifier for the line section.
- *overhead_or_underground (string):* Indicates the type of installation. Accepted values are **OH** (Overhead) or **UG** (Underground).
- *cross_section_sq_mm (float):* Cross-sectional area of the conductor in square millimeters.
- *resistance_ohm_km (float):* Electrical resistance per kilometer in ohms.
- *reactance_ohm_km (float):* Electrical reactance per kilometer in ohms.
- *current_admissable_A (float):* Maximum admissible current for the section in amperes.
- *line_length_m (float):* Physical length of the section in meters.
- *lat_start / lon_start / lat_end / lon_end (float):* Geographic coordinates of the start and end points of the line section, expressed in EPSG:4326 (WGS 84 latitude/longitude)



line_section_name	OverHead_or_UnderGround	cross_section_sq_mm	conductor_type	resistance_ohm_km	reactance_ohm_km	current_admissable_A	line_length_m	lat_start	lon_start	lat_end	lon_end
[illegible]	OH	116	Al-Ac	0.3067	0.352	315	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	OH	116	Al-Ac	0.3067	0.352	315	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	UG	400	Al	0.102	0.108	500	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	OH	116	Al-Ac	0.3067	0.352	315	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	OH	116	Al-Ac	0.3067	0.352	315	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	OH	116	Al-Ac	0.3067	0.352	315	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	UG	240	Al	0.161	0.113	375	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	OH	116	Al-Ac	0.3067	0.352	315	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	UG	400	Al	0.102	0.108	500	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 56: RTTR tool home tab (line topology csv file format)

In the **Import Historical Logs** tab, the user can upload historical measurement data that will be used for the training of forecasting models and enriching the analysis. In this tab, the user selects from a drop down list the relevant line and uploads a .csv file containing historical logs (Figure 57).

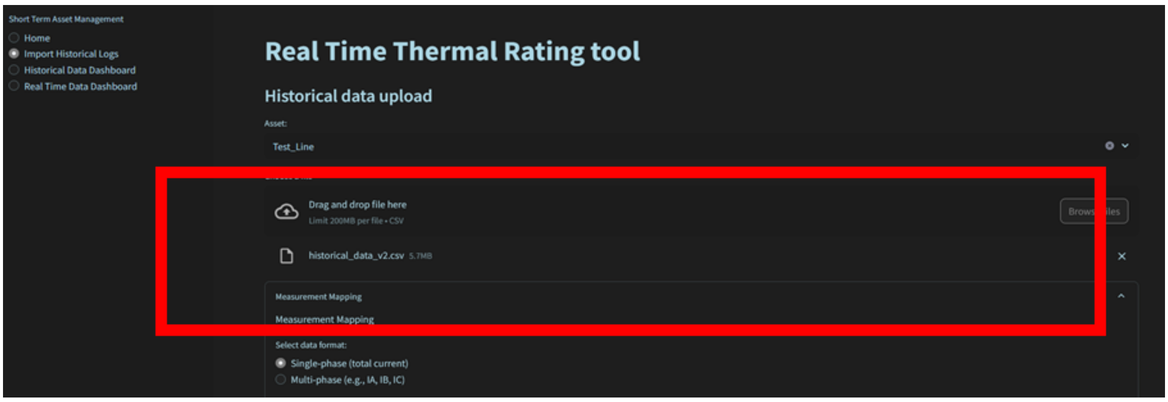


Figure 57: RTTR tool Import Historical logs tab (select line and upload historical measurements csv file).

The system automatically checks the file format to ensure it meets the required specifications. If the format is valid, the data is parsed and stored in the system. If the format is incorrect an error message appears (Figure 58). These historical logs should include current measurements, average or per phase from any other source, e.g. SCADA. Once imported, the data becomes available for model training, analysis, and visualization within the tool.

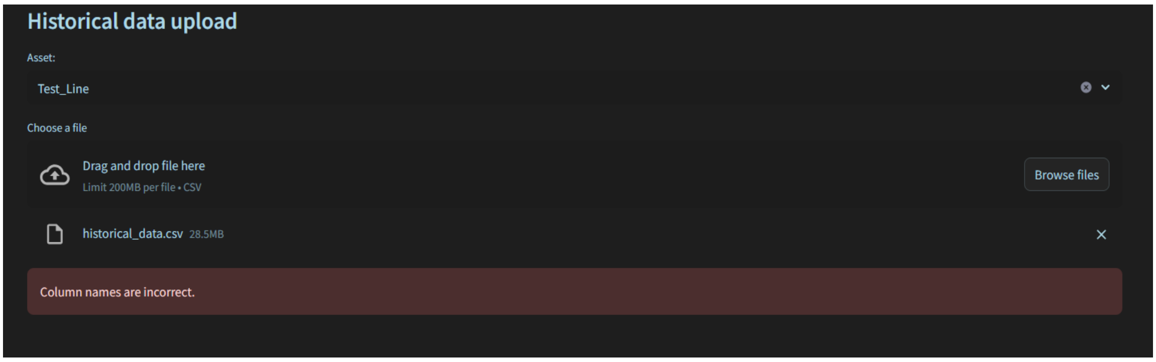


Figure 58: RTTR tool Import Historical logs tab (error message for wrong csv file format).

The measurement file must be provided in **CSV format** with **UTF-8 encoding**. It is used to import sensor or system measurements that are timestamped and associated with a specific measurement type and value.

Each file must include the following three columns, in the specified order:

- **Timestamp**: The exact date and time of the measurement. This must follow the format dd/mm/yyyy hh:mm:ss, e.g., 01/09/2023 05:14:00 in local time.
- **Measurement**: A descriptive string that identifies the type and location of the measurement. For example, "Current (phase R 40kV)".
- **Value**: A numeric (floating point) value representing the recorded measurement.

Timestamp	Measurement	Value
01/09/2023 05:14:00	Current (phase R 40kV)	67.4
01/09/2023 05:14:00	Current (phase S 40kV)	69.3
01/09/2023 05:29:00	Current (phase R 40kV)	79.8
01/09/2023 05:29:00	Current (phase S 40kV)	81.3
01/09/2023 05:44:00	Current (phase R 40kV)	77.7

Figure 59: CSV format on historical logs file

Once the data have been imported successfully, the user has to select whether the data include currents per phase or an average value across three phases (Figure 60). According to the choice, a drop-down list for the selected signals configuration appears, where the user has to select the mapping of signal names to signals, e.g. Current of Phase A is the measurement 'X' in the provided data file.

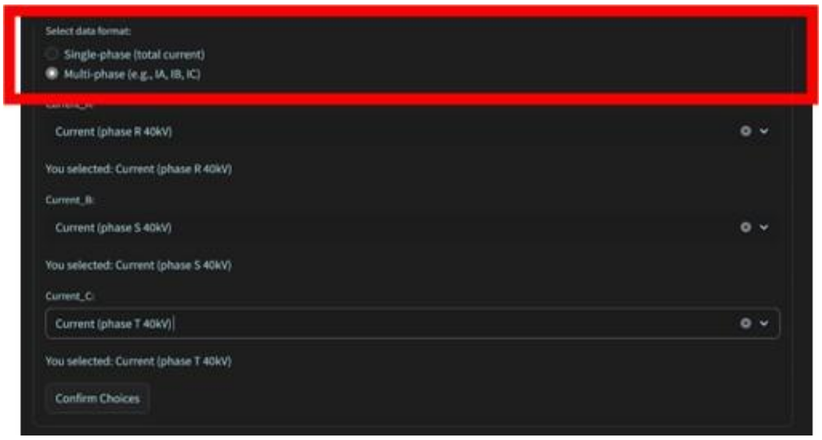


Figure 60: RTTR tool Import Historical logs tab (select current measurement type).

When the mapping is selected by the user and 'confirm choices' button is pressed the mapping is presented to the user (Figure 61). When pressed, the button 'Write data to database' saves the data to the database and starts the re-training process of the ML models for the asset (line) for which the data have been uploaded.

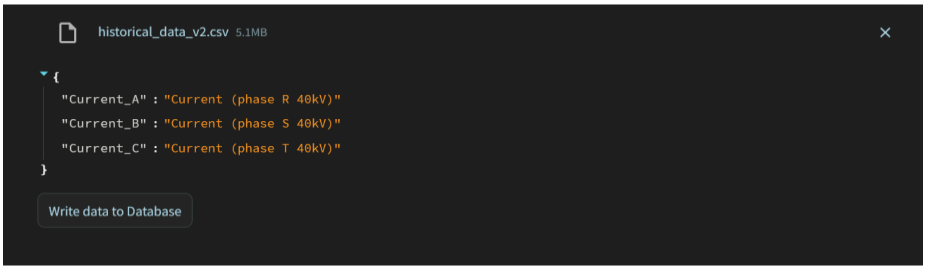


Figure 61: RTTR tool Import Historical logs tab (measurement mapping presentation).

In the **Historical Data Dashboard** tab, the user can view and download historical measurements and tool-generated calculations for offline analysis. To begin, the user selects both the desired time period and the specific asset (line) to visualize the corresponding historical data (Figure 62).

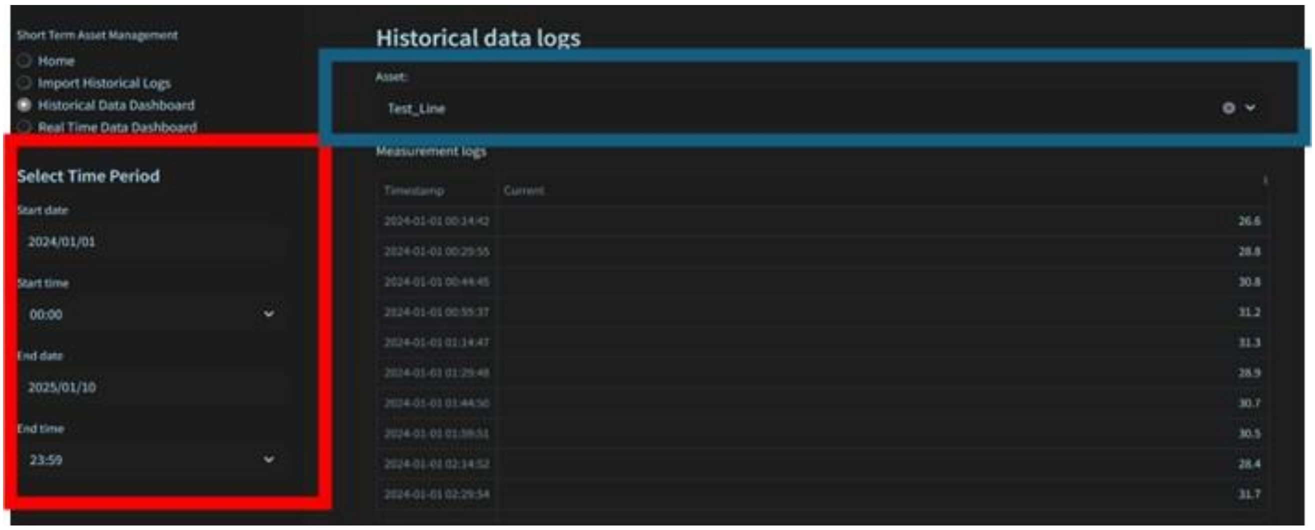
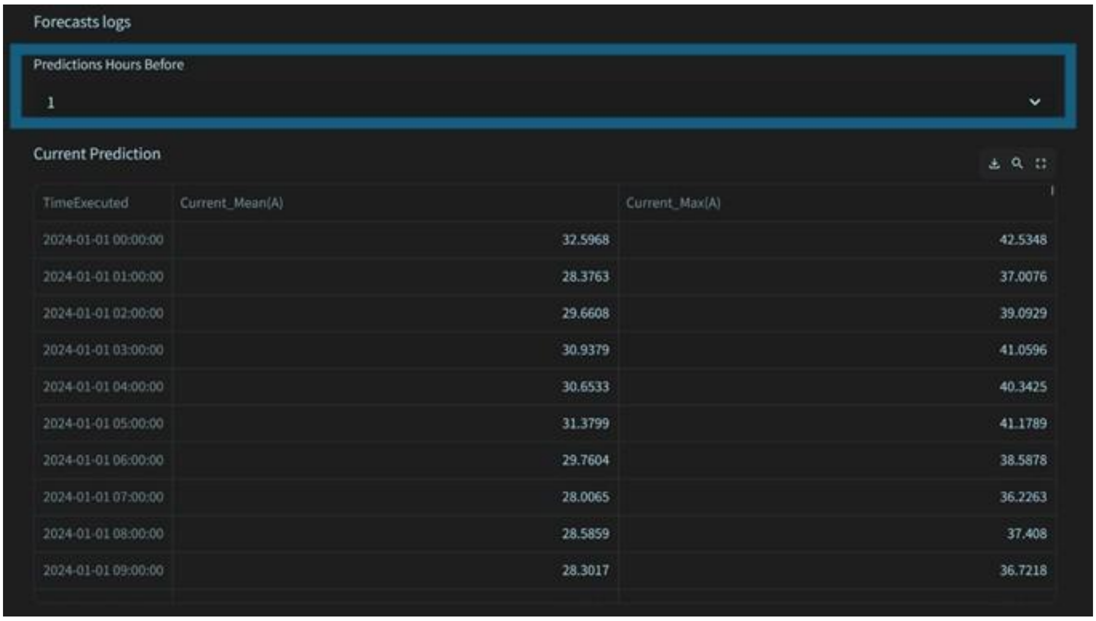


Figure 62: RTTR tool Historical Data Logs Dashboard tab (selection of line and time period).

Once a line and time range are selected, the interface displays multiple data tables, each of which can be downloaded in .csv format. The first table, titled **Measurement Logs**, contains historical sensor data or user-provided data. This includes conductor current—represented as the maximum value across phases when three-phase data is available—and conductor temperature measurements, all aligned with their respective timestamps.

In addition to measurements, the user can access the **conductor's current forecasts**. To do so, a **forecast look-ahead window** must be specified. Forecasts are generated for a 6-hour horizon, meaning that for any given timestamp **T**, the system includes forecast values that were computed at **T-1, T-2, ..., T-6 hours**. The user selects the forecast interval using the **'Prediction hours before'** dropdown menu (Figure 63). For example, selecting **1** will display forecasts that were generated one hour prior to each timestamp shown. This functionality enables users to explore how predictions evolve over time and assess the accuracy of the forecasting models.

The forecast data includes both the **maximum** and **mean** predicted current values for each timestamp (Figure 20). Additionally, based on the selected forecast interval, the user can also view **conductor temperature forecasts** and calculated **loading percentages**—both for mean and maximum current—relative to the maximum allowable temperature for each section of the line (Figure 64). Finally, the user can view the dynamic line rating, as maximum current permitted in Amps, calculated by the tool for the line for the different timestamps (Figure 65).



TimeExecuted	Current_Mean(A)	Current_Max(A)
2024-01-01 00:00:00	32.5968	42.5348
2024-01-01 01:00:00	28.3763	37.0076
2024-01-01 02:00:00	29.6608	39.0929
2024-01-01 03:00:00	30.9379	41.0596
2024-01-01 04:00:00	30.6533	40.3425
2024-01-01 05:00:00	31.3799	41.1789
2024-01-01 06:00:00	29.7604	38.5878
2024-01-01 07:00:00	28.0065	36.2263
2024-01-01 08:00:00	28.5859	37.408
2024-01-01 09:00:00	28.3017	36.7218

Figure 63: RTTR tool Historical Data Logs Dashboard tab (selection of forecasts and visualization of forecast results).

Temperature Prediction

TimeExecuted	section	Temperature_max_C	Temperature_mean_C	Loading_max_%	Loading_mean_%
2024-01-01 01:00:00	A871	3.4457	3.3417	4.0537	3.9315
2024-01-01 01:00:00	A12257	3.491	3.3765	4.1071	3.9723
2024-01-01 01:00:00	A12448	3.5687	3.436	4.1984	4.0424
2024-01-01 01:00:00	A10547	3.395	3.3028	3.9941	3.8857
2024-01-01 01:00:00	A10546	4.4639	4.2249	5.2517	4.9704
2024-01-01 01:00:00	A10545	3.5435	3.4167	4.1688	4.0197
2024-01-01 02:00:00	A871	2.4863	2.369	2.925	2.787
2024-01-01 02:00:00	A12257	3.4901	3.3718	4.106	3.9669
2024-01-01 02:00:00	A12448	3.1514	2.8593	3.7075	3.3639
2024-01-01 02:00:00	A10547	3.3935	3.2986	3.9924	3.8807

Figure 64: RTTR tool Historical Data Logs Dashboard tab (visualization of conductor temperature forecast results).

Rating Prediction

TimeExecuted	Currrent_max_A
2024-01-01 01:00:00	1110.9115
2024-01-01 02:00:00	1115.3196
2024-01-01 03:00:00	1083.3635
2024-01-01 04:00:00	999.9028
2024-01-01 05:00:00	917.7437
2024-01-01 06:00:00	850.6871
2024-01-01 07:00:00	703.0225
2024-01-01 08:00:00	608.4182
2024-01-01 09:00:00	842.7464
2024-01-01 10:00:00	943.6007

Figure 65: RTTR tool Historical Data Logs Dashboard tab (visualization of conductor real time thermal rating results).

Finally, in the **Real-Time Data Dashboard** tab, the users can have live insights into the operational status and predictive analytics for each monitored asset (line). In this tab, the user begins by selecting the desired asset (line) from the available list. Once a line is selected, the interface presents a set of real-time outputs. These include **probabilistic current predictions for the next 6 hours**, based on the latest measurements and forecasting models (Figure 66).

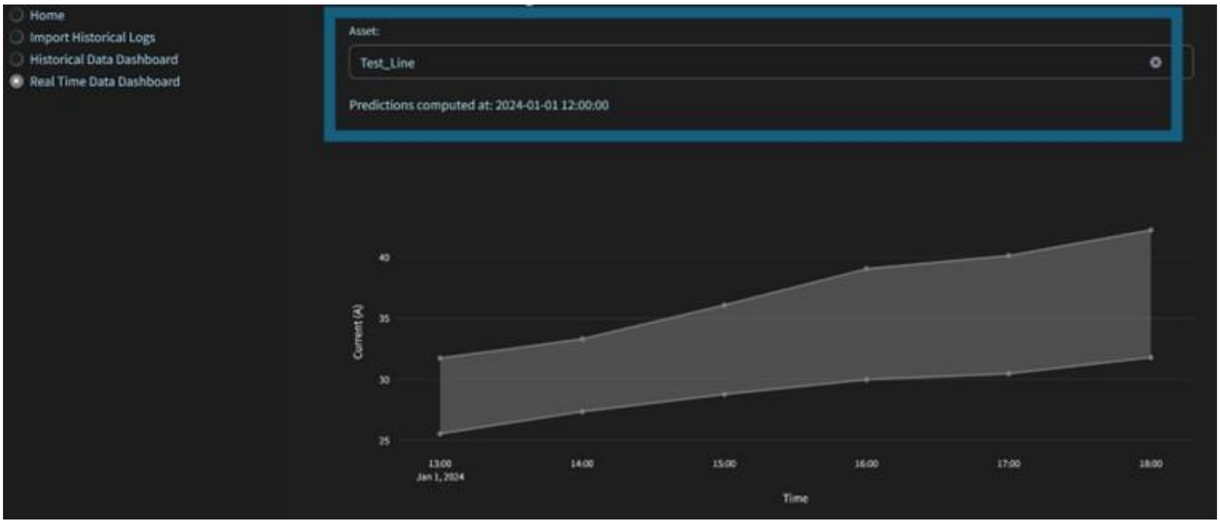


Figure 66: RTTR tool Real Time Data Dashboard tab (selection of line and current prediction results view).

In addition, the dashboard displays the **forecasted conductor temperature** across different sections of the line, visualized directly on a map. This spatial representation allows users to quickly identify sections of the line where thermal limits may be approached or exceeded (Figure 67). Lines would have been colored differently if conductor temperature in any section increases close to the temperature limit.

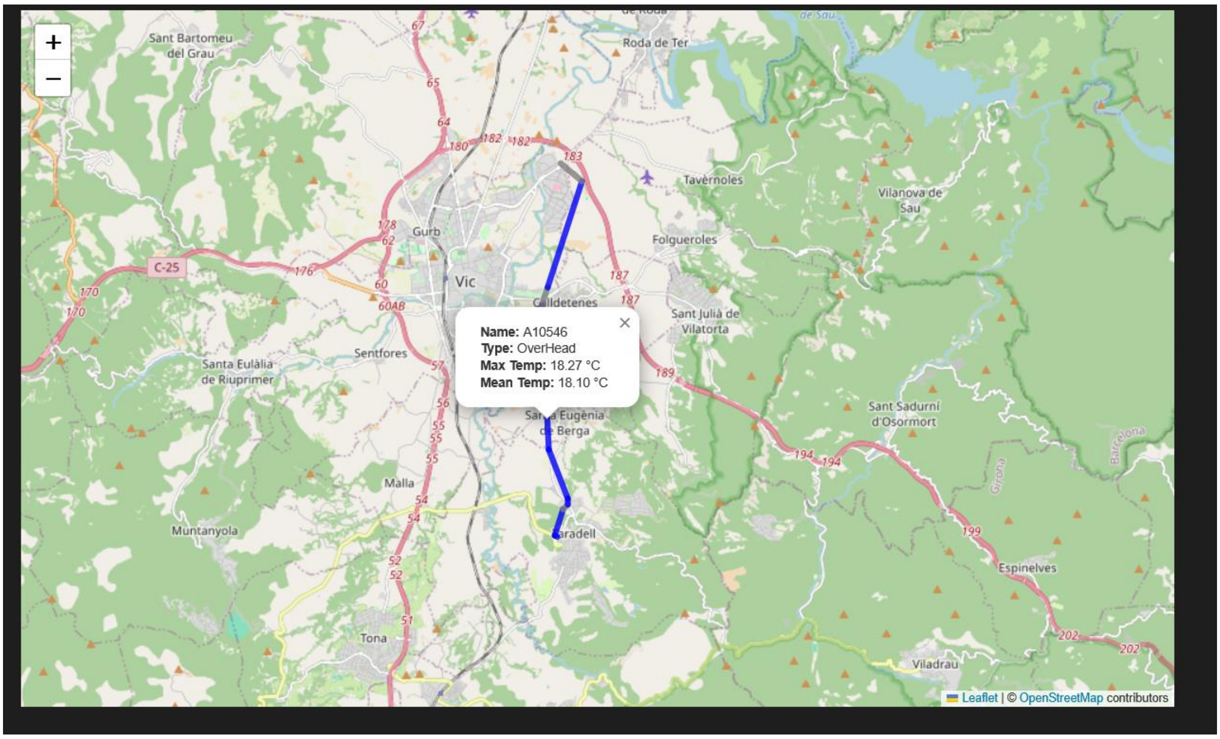


Figure 67: RTTR tool Real Time Data Dashboard tab (conductor temperature visualization on map).

Finally, the tab also provides **real-time thermal ratings predictions** for the next 6 hours (Figure 68). These ratings help operators make informed decisions about load management and system safety in real time.

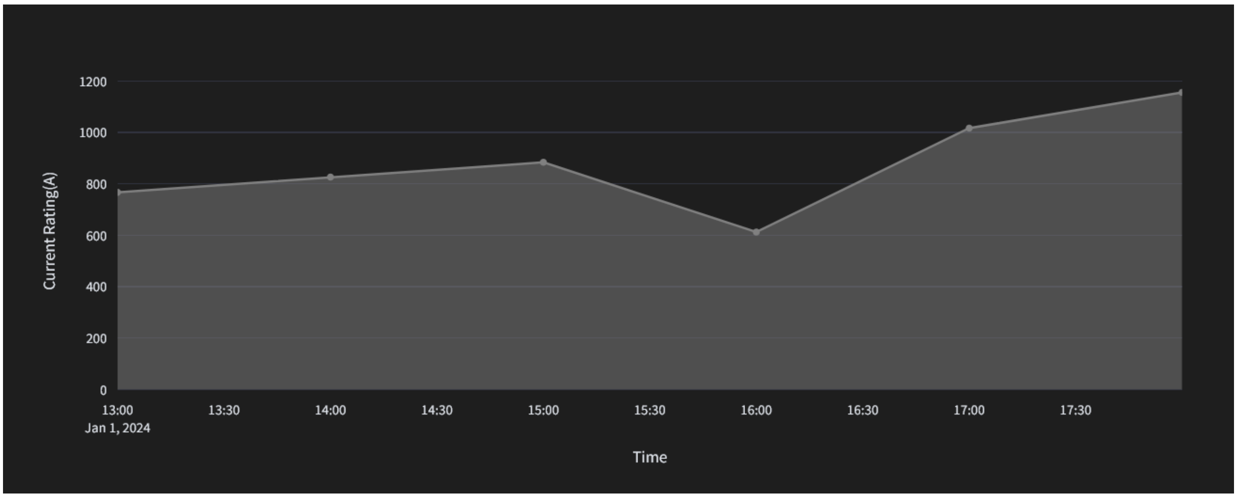


Figure 68: RTTR tool Real Time Data Dashboard tab (Real Time Thermal Rating forecast for 6 hours ahead).

5 CONCLUSIONS

The modules described in this document make significant advancements in technologies for Distribution System Operators (DSOs). The developed tools aim to enhance the accuracy, reliability, and efficiency of power distribution networks.

The Topology identification tool focus on an innovative task, the semi-automatic building of the LV network topology by making use of the smart meter measurements. This could facilitate the DSO tasks of deploying and start managing low voltage networks.

Two of the modules, namely the **Topology detection** and the **Fuse burn detection for early outage and islanding recovery** focus on detecting errors in the topological database that might lead to security problems and suboptimal operation of the grid.

The last module linked to the topology is the **real-time thermal rating module**, that is focusing on determining the real ampacity of power lines given actual the climate conditions.

The two **state estimation** versions defined could also assist DSO in the process of safely manage the grid, by proving enhanced observability based on new measurements coming from PMUs and pseudo-measurements calculation.

Finally, two processes are designed to complement the DSO duties: the **critical point detection tool** can be seen as a grid planification tool that helps identifying weakness in **the grid. The Short term analysis of the impact of DER in the Distribution grid**, will warn DSO upon the detection of security problems linked to DER assets.

It is noteworthy that the modular approach ensures that the modules can be adapted and scaled according to the specific needs of different DSOs and network configurations.

From this moment, to continue the work done here, the focus will be put on finalizing the integration of the required data sources from the different pilots in order to be ready for the demonstration activities. These integration activities will be reported in *Deliverable 6.1 Deployment and demonstration plan.*

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6.2 Acronyms

Table 3. Acronyms

Acronym	Explanation
AMI	Advanced Metering Infrastructure
DER	Distributed Energy Resource
RT	Real-Time
RTTR	Real-Time Thermal Rating
OPF	Optimal Power Flow
SCADA	Supervisory Control and Data Acquisition
DSSE	Distribution system state estimation
DSO	Distribution System Operator
TSO	Transmission system operator
PSSE	power system state estimation
ReLU	Rectified Linear Unit
RNN	Deep recurrent neural networks
PMU	Phasor measurement unit
LV	Low voltage
MV	Medium voltage
HV	High voltage
NN	Neural network
DNN	Deep neural network
ADN	Active distribution network
TI	Topology Identification
SE	State Estimation

7 ANNEX

7.1 Implementation details of State Estimation

Since loads and generators are independent among each other, for each one of them, two DNN models are required: One for active and other for reactive energy modelling. This means that the amount of DNN models required could be really huge (at least 2 x number of supply points) and thus deserves a specific management strategy.

Each neural network is trained using historical data from assets measurements (power curves from smart meters) and exogenous variables that might impact the behavior (weather information and calendar type of day). The models obtained are able to predict future behavior given the last measurements observed and the predicted weather and calendar information, but the train process can be really time consuming for large historical datasets and should be re-trained periodically. As a result of this, we have selected a strategy where DNN models are trained and stored as part of an offline task running periodically and the rest of the processes simply obtain the last version of the required models from the storage and use them to perform the required estimations:

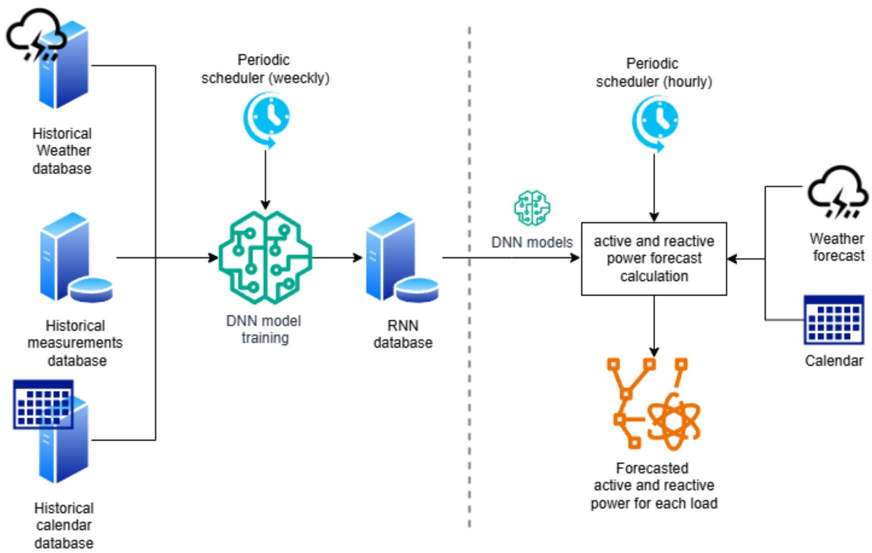

Figure 69: DNN Model Training and usage in DSS calculations.

The left-hand side of the diagram illustrates how the DNN models are periodically trained and stored, whilst at the right-hand side, the active and reactive power forecasts are generated using the most up-to-date DNN model existing.

The DNN models for active and reactive power prediction are built using the NeuralProphet [9] framework, due of the features and accuracy offered by this framework for the time series forecasting.

The field of time series forecasting was traditionally dominated by statistical techniques. Classical models such as Auto-Regressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) have been well studied and provide interpretable components. However, their restrictive assumptions and parametric nature limit their performance in real world applications. A skillful forecasting expert can transform data and combine algorithms to satisfy specific conditions for better performance. This requires deep domain knowledge in the application itself and in classical time series modelling. Despite its problems, statistical techniques perform better than machine learning based models (neural networks) in time series forecasting.

NeuralProphet is a hybrid forecasting framework based on PyTorch and trained with standard deep learning methods, making it easy for developers to extend the framework. Local context is introduced with auto-regression and covariate modules, which can be configured as classical linear regression or as Neural Networks. Otherwise, NeuralProphet retains the design philosophy of Meta Prophet [10] framework and provides the same basic model components. Its hybrid nature combines the benefits of both the statistical and the neural network approach to better predict time series behaviour.

InfluxDB [11] database has been selected for the storage of historical measurements. It is an open-source time series database designed to efficiently store, query, and analyse high volumes of timestamped data such as metrics, events, and sensor readings:

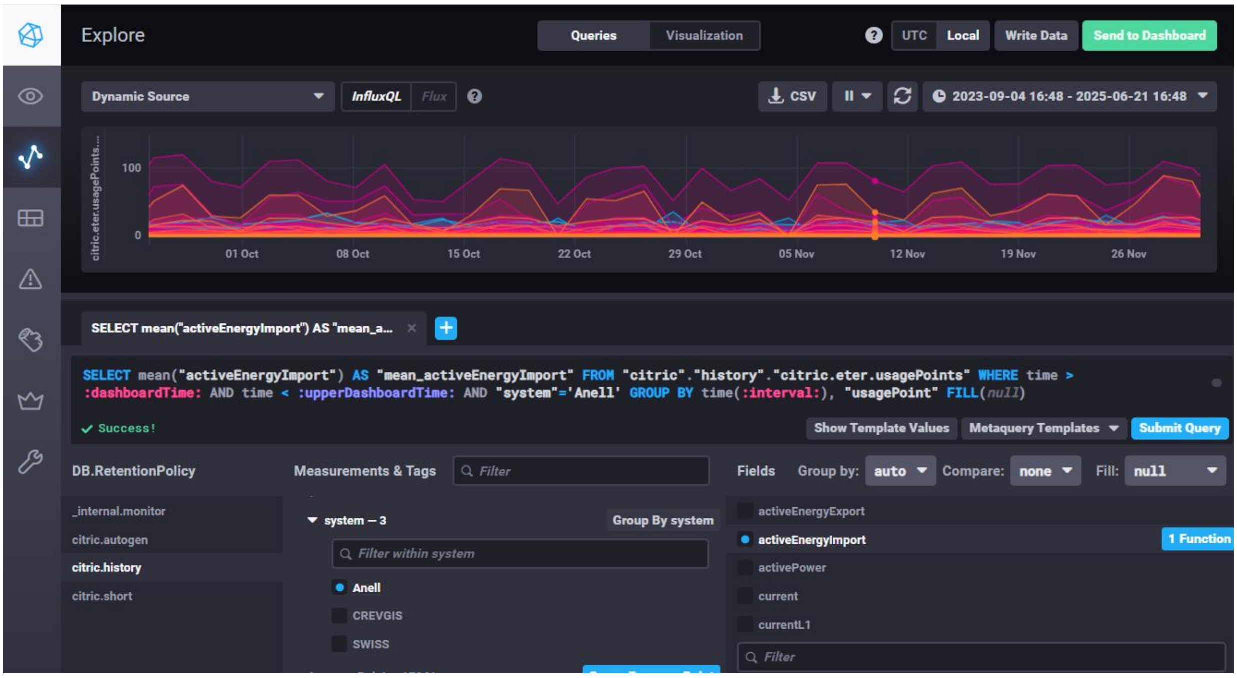

Figure 70: InflusDB view

For the storage of the DNN models the open-source platform MLflow [12] is used. It is designed to manage the end-to-end machine learning lifecycle, providing a suite of tools to facilitate experiment tracking, model versioning, packaging, and deployment in a reproducible manner. MLflow supports any machine learning library or programming language and integrates seamlessly with popular frameworks:

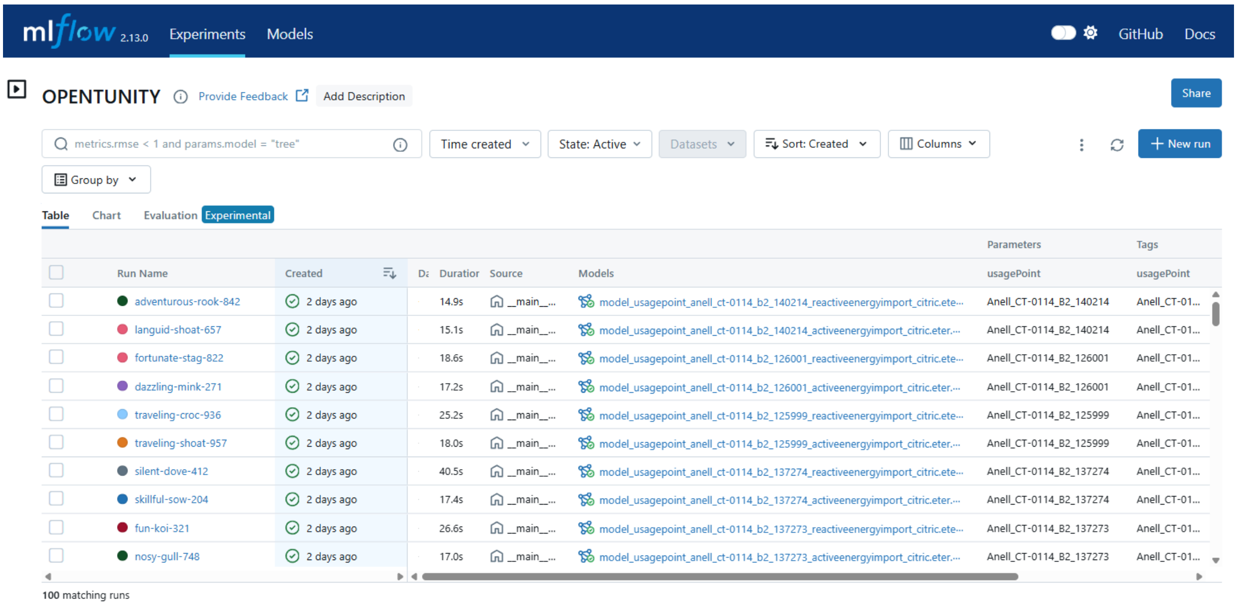

Figure 71: MLflow view

In the screenshot, usage points DNN stored models can be seen and, for each of them, active and reactive power models are stored.

The generation of these pseudo measurements using the DNN models is just the first step. Periodically, the DSSE will be fed with these pseudo measurements and the real observed measurements. The internal DSSE algorithm will balance the pseudo measurements so that **the resulting power flows matches the real observed measurements, with the minimal number of changes in the pseudo measurements**.

7.1.1 Real time state estimation.

In the case of **real time state estimation**, the data from energy meters power curves is not available yet but only pseudo-measurements and real time sensor data: SCADA data (normally obtained from RTUs at the substations) and measurements from PMUs (deployed across the grid, and normally scarce). For this version of the state estimation algorithm, PMUs will not be available, so we have counterbalanced for this lack with different alternatives:

- **Real-time Measurements coming from domestic sensors** deployed at certain delivery points (houses or tertiary building) will be used. These sensors are used in other OPENTUNITY workpackages (WP4) for enabling some end-used based electric grid functionalities, like demand response, NILM or market participation. In our case we will take advantage of the continuous real time measurement transmission toward the control center that these devices perform, using IoT mechanisms. Specifically, we will use the point of delivery measurement readouts.
  The device selected and deployed for this purpose in OPENTUNITY is the Shelly EM Wi-Fi-operated energy meter. This device is a clamp capable of measuring electrical parameters with an accuracy of 99%:

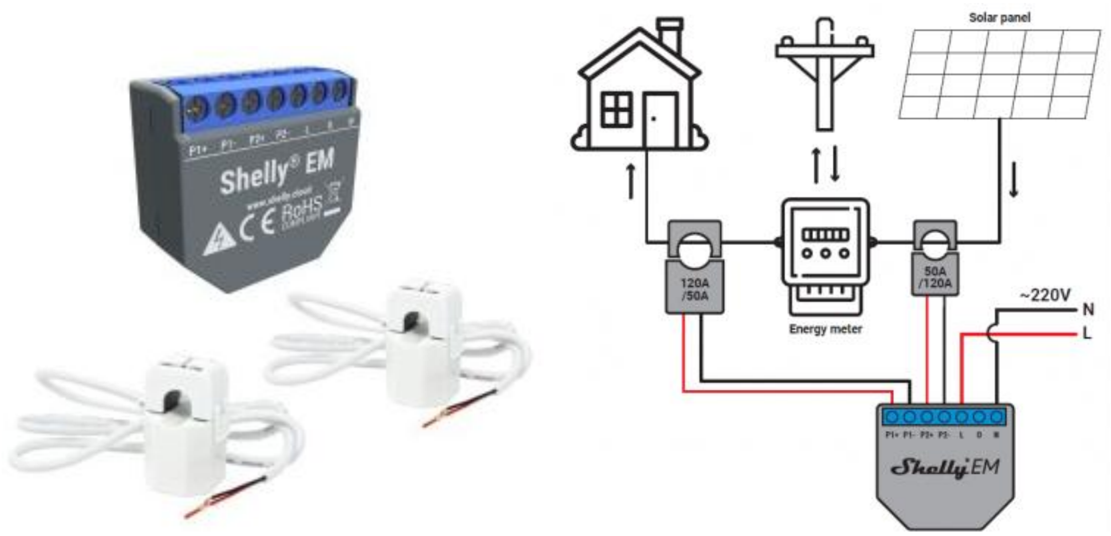

Figure 72: Shelly EM details and connectivity

Shelly EM devices are deployed at some selected locations, clamping the electrical cable just after the energy meter, so that the whole household electrical measurements are obtained and sent to the control center via WIFI. The same structure can be used to measure domestic solar panel generation.

- **Real time data coming from energy meters**. One of the main purposes of distribution operators is to obtain the necessary data from energy meters to allow for end user billing. These energy meters are ubiquitous, as they monitor every delivery point in the grid, and in the last decades there has been a rollout across Europe to replace them with 'smart' energy meters. The smart meters differ from previous generation of meters (among other things) in the sense that they can be interrogated from remote for gathering the necessary data for billing. This implies lots of savings compared to the previous process of manual data gathering. The infrastructure used for this is called advanced metering infrastructure (AMI):

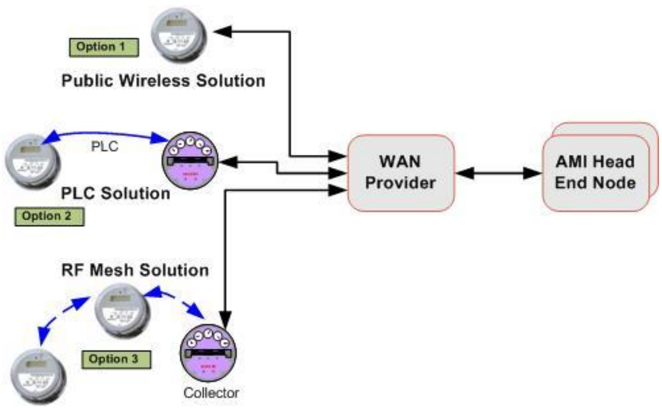

Figure 73: General AMI set up with communication options

The picture above depicts different options for the AMI set up. There is always the need of an intermediate infrastructure that gathers and adapts data from the wide area network (WAN) defined by the network of smart meters toward the AMI head end node at the DSO premises, but there are alternatives for it:

- **The first option** is to have smart meters with the capacity of connecting to publicly available communication networks, normally GPRS/2G/3G/4G wireless networks. This is the most convenient option, as the network is available and features high bandwidth and low latency, but the cost is prohibitive, and its use is marginal for domestic energy meters.
- **The second option** is to use the existing power lines and cables for data transmission. This type of communication is called power line communication (PLC).
  In this option, there are *data concentrators* equipment deployed (normally at the MV/LV substations), each one physically connected to a specific cable or wire that spans across a certain low voltage network:

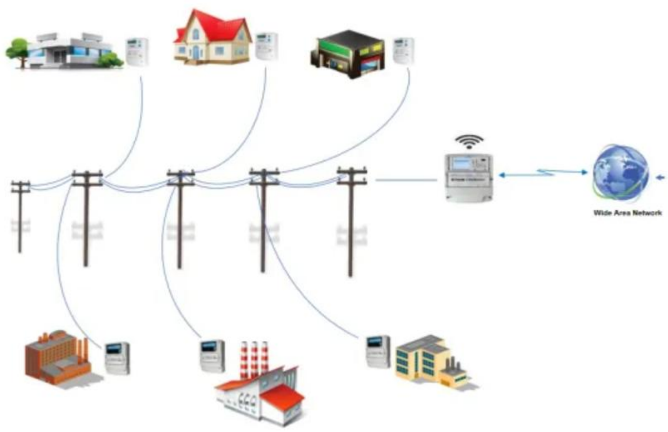

Figure 74: AMI with PLC communication.

The purpose of the concentrators is to periodically interrogate the smart meters to gather its power curves. This option is relatively cheap to implement because the power lines are already owned by the DSO, but the bandwidth is low and the latency high. These performance problems do not hinder the adoption of this technology, as the DSO normally just requires aggregated monthly power curves from the smart meters. For this reason, it is the preferred solution by the DSO operators and the most commonly used.

- **The third option** implies the use of low range radio frequency (RF) meshed networks. This technology use the radio frequency to transmit the data, with the particularity that in this networks, just a small subset of the households energy meters can directly reach the WAN gateway and deliver the data, but the rest of the energy meters must transmit the data to neighbor energy meters that will re-transmit this data until eventually it reaches the WAN gateway. This mesh of energy meters is self-organized and thus relatively cheap to set up and maintain, but the bandwidth is low and the latency high. Currently, it is not broadly used for domestic energy meter communication, but its use is increasing, especially for dense areas.

As previously described, AMI primarily focuses on getting monthly power curves from energy meters, but there is always the possibility to obtain 'real' time measurements from the meters. The resolution and accuracy of the real time measurements obtained depends on the AMI network option selected, but in any case, it is always worse than SCADA and PMU obtained measurements, so post-processing is needed to ensure quality of data.

In OPENTUNITY we will focus on PLC AMI networks, as it is the most common option. In this type of networks, the data concentrators are configured to interrogate the smart meters for sending power curves once a month, but other schedules are also possible. We will configure the data concentrators to interrogate the smart meters at the LV grid for real time measurements (P, Q, I & V) with the maximum possible frequency. This data is known in DSO jargon as **test cycles**, and the frequency of the data obtained for each smart meter in a PLC network depends on different factors, like number of smart meters in the network, power line interferences, limitations in smart meter power electronics, etc. Typical results spans from one real time measurement per minute to one real time measurement per 7-8 minutes, for each smart meter.

In summary, for grid state estimation of current, real time the following sources of information are used: The **pseudo measurements**, real time **SCADA data**, real-time **Measurements coming from domestic sensors** and Real time **data coming from energy meters**. Even though not all data will be assigned the same "quality".

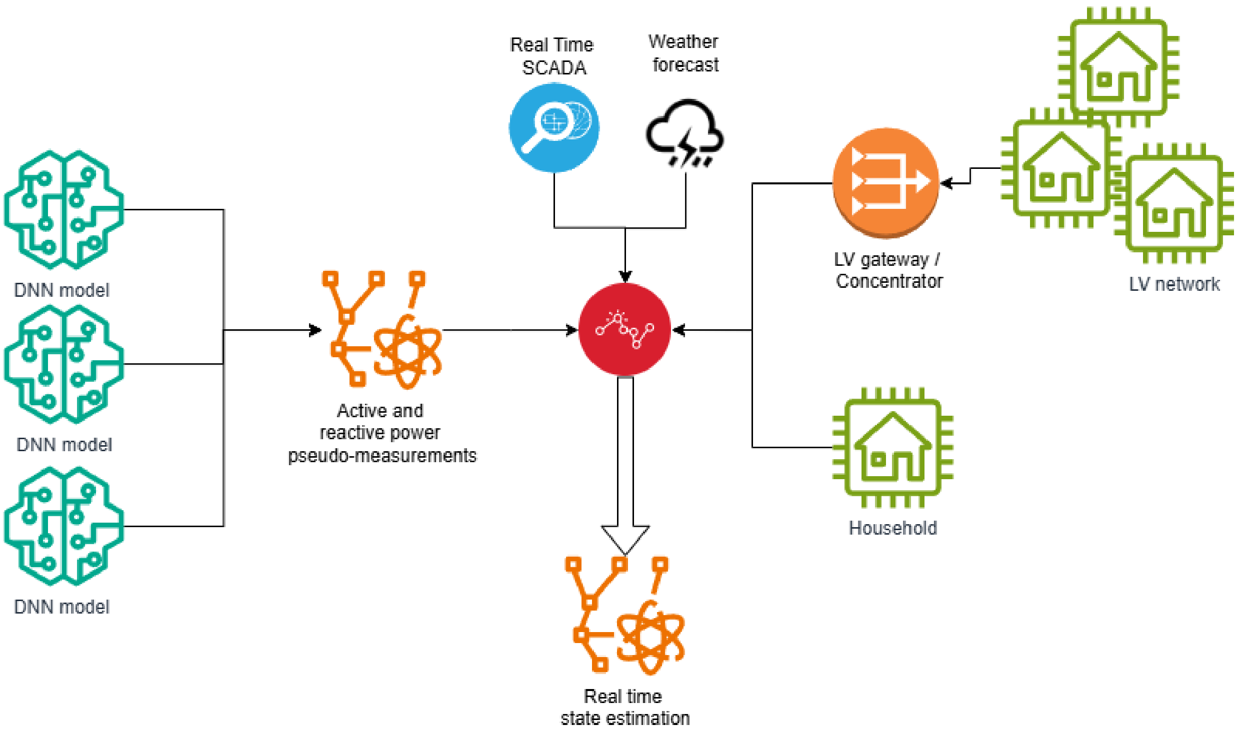

Figure 75: Overall schema of State estimation

As previously mentioned, DSSE algorithm will balance the available measurements so that the resulting power flows calculation converges and the number of changes in the measurements are minimized. The balance of the measurements means reducing or increasing them according to certain limits. Basically, each measurement is assigned an accuracy value in the form of a standard deviation. Typical measurement errors are 1 % for voltage measurements and 1-3 % for power measurements. Nevertheless, pseudo measurements and the "real" time measurements from LV that are not precisely time aligned, will be given a higher standard deviation.

There are different state estimation methods in literature [13]:

- **WLS (Weighted Least Squares, Newton-Gauss)** The most widely used state estimation method in power systems. WLS minimizes the sum of the squared residuals between measured and calculated quantities, weighing each measurement by its estimated accuracy. The Newton-Gauss algorithm iteratively linearizes the nonlinear equations involved and updates the state estimate until convergence. It is efficient and statistically optimal when measurement errors are Gaussian, but it is sensitive to outliers or gross measurement errors.
- **WLS with Zero Injection Constraints**. An extension of WLS that incorporates nodes (buses) with known zero power injection (no generation or load) as equality constraints. This can increase accuracy and observability by utilizing available network knowledge.
- **LP (Linear Programming) with LAV (Least Absolute Value)** In this context, LP is used to implement the Least Absolute Value (LAV) estimator. Unlike WLS, which minimizes the sum of squared errors, LAV minimizes the sum of the absolute values of the residuals. It is more robust to outliers compared to WLS, since large errors do not get squared.
- **IRWLS (Iteratively Reweighted Least Squares)**. This is an advanced scheme that enhances WLS by reducing the impact of outlier measurements. At each iteration, residuals are used to update the weights for the least squares minimization; large residuals (potentially outliers) get less influence.
    - **irwls + wls**: Applies reweighting to classic WLS.
    - **irwls + shgm**: Uses the Schweppe-Huber Generalized M-estimator[4] reweighting strategy for outlier robustness.

In the case of OPENTUNITY, and due to the relatively high inaccuracies in the pseudo measurements, the simplest WLS estimators have proven to be unable to identify feasible solutions in most of the cases, so we have selected the **IRWLS + shgm** algorithm.

There is a minimum number of available measurements necessary for the regression to be mathematically possible. Assuming the network contains n buses, the network is then described by $2n$ variables, namely voltage absolute values and voltage angles. A slack bus serves as the reference; its voltage angle is set to zero and is not altered in the estimation process. The voltage angles of the other network buses are relative to the voltage angles of the connected slack bus. The state estimation therefore has to find $2n - k$ variables, where k is the number of defined slack buses. The minimum number of measurements m_{min} needed for the method to work is therefore:

$$m_{min} = 2n - k$$

In our case, there will be pseudo measurements for the active and reactive power for each of the loads and generators of the grid. This will allow to perform power flow based on it and thus obtaining pseudo measurements for the voltage and angle at all the buses of the grid. This, along with the real measurements is enough to perform the state estimation, even with no further real time

[4] **SHGM (Schweppe-Huber Generalized M-estimator)**
A robust statistical estimator that down-weights large residuals according to a specific function (the Schweppe-Huber function). It is particularly effective at reducing the influence of bad or grossly erroneous data points.

measurements. The case of not having real time measurements but only estimated loads and voltages is equivalent to the calculation of the optimal power flow using the forecasted values for the loads, but in order to obtain accurate results, some real time measurements will be needed. **The next deliverables in WP7**, will analyze the accuracy of the method given the amount of real time measurements available.

Finally, it is noteworthy that:

Past periods state estimation for non-technical loses calculation: This is described in section *4.8: Non-technical losses detection* of deliverable D5.4

Future periods state estimation. This is described in section 4.7 Short term analysis of the impact of DER in the Distribution grid.

Scenario-based state estimation. This is described in section 4.6 - Critical point detection tool.

7.2 Meter placement – Greek demo

The core concept of the enhanced SE tool of the Greek demo is the design and implementation of DSSE using a strictly learning-based approach. In this context, high-performing DNN-based TI and SE services are enabled using exclusively synchrophasor data, which meet the higher standards of measurement accuracy and synchronization. However, to ensure the cost-effective utilization of synchrophasors for grid monitoring, PMU installations must be kept to a minimum. To this end, an optimal meter placement methodology has been developed to identify a minimal set of PMUs for deployment at the Greek demo site, ensuring that predefined TI and SE performance criteria are fulfilled.

The generic optimal meter placement problem is cast as a grouped feature selection task within a supervised Machine Learning (ML) framework. In this formulation, each PMU corresponds to a distinct group of features, typically comprising one complex bus voltage and one complex branch current. The feature selection process is driven by a novel supervised ML approach that integrates the Random Forest (RF) algorithm with Recursive Feature Elimination (RFE), allowing the identification of the most informative PMU placements based on data-driven importance scores.

Below, a concise step-by-step overview of the proposed methodology is provided.

1. Dataset and grouping: the set of training data is generated and feature indices are partitioned into non-overlapping groups, with F_i representing the i-th physical meter, e.g. PMU,
2. RF training: An RF ensemble (regression for state-estimation error, or classification for topology inference) is trained on the current set of meters. RF aggregates many decision trees built on bootstrap samples, giving robust importance scores.
3. Feature-to-meter importance aggregation: For every individual feature j the RF outputs an importance I_j (impurity reduction: Gini for classification, MSE for regression). Each meter score is the sum over its features' importance scores $S_i = \sum_{j \in F_i} I_j$.
4. Recursive feature elimination loop: the meter with the smallest importance score is identified and, then, removed from the current set of meters. Steps 2-4 are iteratively executed until the desired number of meters (or just one meter) remains.

5. Ranked output: the resulting, successive set of meters form a full ranking–from most to least informative–yielding a principled placement schedule. In practical terms, the designer stops at the first k meters that meet TI/SE accuracy requirement, which are quantified by means of desired performance indicators (e.g., mean absolute percentage error) and cost restrictions.

This combined RF-RFE strategy comprises a powerful solution for designing metering systems as it leverages:

i. the nonlinear, interaction-aware feature scoring of the RF algorithm and

ii. the greedy yet effective pruning of RFE, producing a data-driven, meter-level ranking without combinatorial search.

The block diagram of the developed placement methodology is presented in Figure 76. Once this process is finalized the order of the meters in descending importance score order is extracted. Using this ordered set DNNs are iteratively trained with a new feature set, augmented with the next important meter's features, until the corresponding thresholds are reached.

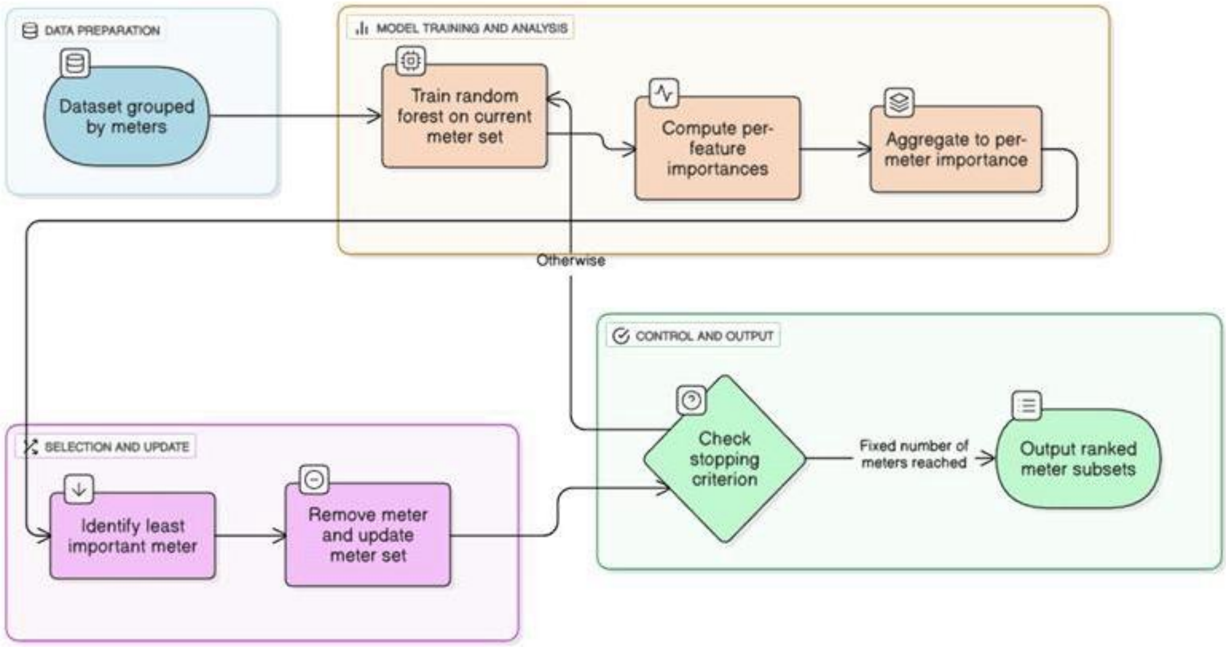

Figure 76: Block diagram of the optimal meter placement scheme

A challenge met in the design phase is the determination of measurement configuration per PMU. More specifically, measuring current phasors in distribution grids is a rather complicated task. It is practically infeasible to obtain line current flow measurements downstream primary substations especially in overhead networks, since the available switching and protection devices which could host PMUs, are limited. As a result, the required facilities must be constructed from scratch, thus, inferring high cost, mainly referring to the purchase of current and voltage transformers, (CTs/VTs) and unreasonable labour effort.

As reported in [14], the most convenient option in case of distribution networks is to place PMUs at locations with pre-existing CTs/VTs, such as the secondary, low voltage side of service transformers. Therefore, by adopting this solution, the current measurements delivered by an installed PMU refer to bus injected/ absorbed currents.

Based on the above analysis, two alternative PMU measurement schemes have been considered. Under the assumption that a PMU is installed at bus *i*, the first scheme involves measuring the phasors of the bus voltage along with the current flowing through one incident branch. The second scheme involves measuring the phasors of the bus voltage and the injected current at the same bus. Candidate installation points are load buses, each corresponding to a service transformer.

Moreover, leveraging the flexibility of the developed methodology to accommodate various measurement types, a third measurement scheme has been explored at the request of HEDNO. This scheme involves the allocation of additional AMDs installed on the LV side of service transformers to record load consumption, supplementing the pre-existing units. While these data will not be used directly for TI and SE, they will serve as a validation source for the outputs of the respective services.