



Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

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Table of Contents

Executive Summary.....	11
1 Introduction.....	13
1.1 Objectives.....	13
1.2 Structure of the document.....	13
2 TwinEU's contribution to digital twin applications Grid operation and planning.....	14
2.1 AI Agent for Grid State Forecasting and Remedial Action Identification.....	14
2.2 DT for generation of synthetic series of renewable resources.....	14
2.3 DT-based N-1 contingency analysis.....	15
2.4 DT-enabled new RES integration validated plan in the MV grid.....	15
2.5 DT-based grid maintenance planning activities.....	16
2.6 Long term flexibility in MV.....	16
2.7 Flexible EV Connections.....	17
2.8 DT-Enables Flexible Connections through Local Flexibility Markets.....	18
3 Methodological approach for the implementation of the DT Federation-enabled Use Cases.....	20
3.1 REE's transmission grid.....	20
3.1.1 Overview of REE's Transmission Grid.....	20
3.1.2 Use Cases Related to REE.....	21
3.1.3 Methodology for Implementation.....	21
3.1.4 Testing Scenarios and Performance Metrics.....	25
3.2 Cuerva's distribution grid.....	43
3.2.1 Overview of Cuerva's distribution Grid.....	43
3.2.2 Use Cases Related to Cuerva.....	44
3.2.3 Methodology for Implementation.....	45
3.2.4 Testing Scenarios and Performance Metrics.....	50
3.3 ANELL's distribution grid.....	56
3.3.1 Overview of ANELL's distribution Grid.....	56
3.3.2 Use Cases Related to ANELL's grid.....	57
3.3.3 Methodology for Implementation.....	58
3.3.4 Testing Scenarios and Performance Metrics.....	58
4 Conclusions.....	95
4.1 Summary of Achieved Results.....	95
4.2 Limitations and Lessons Learned.....	95

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

4.3	Recommendations for Future Work.....	96
References		97
Annex A	Downscaling Techniques for Meteorological data.....	100
A.1	Introduction.....	100
A.2	Downscaling approaches.....	100
A.2.1	Dynamic Downscaling	100
A.2.2	Statistical Downscaling.....	101
A.2.3	Machine Learning Downscaling	102
A.2.4	Hybrid Approaches.....	102
A.2.5	Emerging Approaches	103
A.3	Comparative Assessment of Downscaling Approaches.....	103
A.3.1	Accuracy, reliability and extremes	104
A.3.2	Renewable-energy and power-system suitability.....	105
A.3.3	Data requirements and transferability.....	105
A.3.4	Scalability, ease of implementation, explainability and cost	105
A.4	Recommended Approach for the DT.....	106
A.5	Conclusions.....	107
Annex B	Further test cases for UC-Ib07	108

List of Figures

Figure 1. Transmission Grid Digital Twin use cases planning developed by REE and CIRCE.....	21
Figure 2. Flowchart AI Agent.....	22
Figure 3. Flowchart synthetic series generator	24
Figure 4. Initial state: 7 undervoltage violations detected.	27
Figure 5. AI Agent calculation	28
Figure 6. Final state: 2 undervoltage violations detected	28
Figure 7. Target Definition Interface - TC Ib02.1.....	31
Figure 8. Data download interface	32
Figure 9. Request Record – TC Ib02.1	32
Figure 10. Results Parquet dataset	33
Figure 11. Target Definition Interface - TC Ib02.2	34
Figure 12. Future scenarios results.	35
Figure 13. Request Record – TC Ib02.2	36
Figure 14. Results Parquet dataset	37
Figure 15. Target Definition Interface - TC Ib02.3	38
Figure 16. Synthetic series request received from user	39
Figure 17. Request Record – TC Ib02.3	40
Figure 18. Results Parquet dataset	41
Figure 19. Histogram – Manhattan distance	41
Figure 20. Measurement map for the Cuerva’s living lab	43
Figure 21. Cuerva’s grid use cases development plan	46
Figure 22. ANELL's Distribution Network Digital Twin development plan.....	58
Figure 23. ETER scenario selection.	60
Figure 24. ETER line selection for N-1 contingency analysis calculation.	61
Figure 25. ETER topology status after N-1 scenario selection.	61
Figure 26. ETER scenario selection.	64
Figure 27. ETER bus/substation selection for hosting capacity calculation.....	65
Figure 28. ETER hosting capacity results per bus.....	65
Figure 29. Hosting capacity map with ESTABANELL hosting capacity information.	66
Figure 30. ETER scenario selection.	68
Figure 31. ETER bus/substation selection for hosting capacity calculation.....	69
Figure 32. ETER hosting capacity results per bus.....	69

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Figure 33. Hosting capacity map with ANELL hosting capacity information.	70
Figure 34. ÉTER GUI, forecast tab. SER-002.	73
Figure 35. ÉTER GUI, scenario switch closure. SER-002.	73
Figure 36. ÉTER GUI, scenario update with new changes. SER-002.	74
Figure 37. ÉTER GUI, N-1 Contingency Analysis module. SER-002.	74
Figure 38. ÉTER GUI, N-1 Contingency Analysis subscenarios. SER-002.	75
Figure 39. Forecast evolution of the different substations during maintenance.	75
Figure 40. Forecast evolution of substation CT-0954 during maintenance.	75
Figure 41. P2P offers in the Local Trading System (based on XBID)	78
Figure 42. Matched offers notification	79
Figure 43. Scenario creation in ÉTER	79
Figure 44. Scenario selection for parameterising the transaction.	80
Figure 45. Scenario parameters introduces, power flow ran and scenario updated and stored in ÉTER.	80
Figure 46. Scenario simulation with multiple transactions.	81
Figure 47. validated scenarios consultation.	81
Figure 48. ÉTER GUI, forecast tab. CT-0259.	109
Figure 49. ÉTER GUI, scenario switch closure. CT-0259.	110
Figure 50. ÉTER GUI, scenario update with new changes. CT-0259.	110
Figure 51. ÉTER GUI, N-1 Contingency Analysis module. CT-0259.	111
Figure 52. ÉTER GUI, N-1 Contingency Analysis subscenarios. CT-0259.	111
Figure 53. Forecast evolution of substation CT-1030 during maintenance.	112
Figure 54. Forecast evolution of substation CT-0954 during maintenance.	112
Figure 55. ÉTER GUI, forecast tab. CT-0265.	115
Figure 56. ÉTER GUI, scenario switch closure. CT-0265.	115
Figure 57. ÉTER GUI, scenario update with new changes. CT-0265.	116
Figure 58. ÉTER GUI, N-1 Contingency Analysis module. CT-0265.	116
Figure 59. ÉTER GUI, N-1 Contingency Analysis subscenarios. CT-0265.	117
Figure 60. Forecast evolution of substation CT-0568 during maintenance.	117
Figure 61. Forecast evolution of substation CT-0944 during maintenance.	117
Figure 62. ÉTER GUI, forecast tab. CT-0620.	120
Figure 63. ÉTER GUI, scenario switch closure. CT-0265.	120
Figure 64. ÉTER GUI, scenario update with new changes. CT-0265.	121
Figure 65. ÉTER GUI, N-1 Contingency Analysis module. CT-0265.	121

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Figure 66. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0265.....	122
Figure 67. Forecast evolution of substation CT-0113 during maintenance.....	122
Figure 68. Forecast evolution of substation CT-0114 during maintenance.....	122
Figure 69. ETER GUI, forecast tab. CT-0458.	125
Figure 70. ETER GUI, scenario switch closure. CT-0458.....	125
Figure 71. ETER GUI, scenario update with new changes. CT-0458.	126
Figure 72. ETER GUI, N-1 Contingency Analysis module. CT-0458.	126
Figure 73. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0458.....	127
Figure 74. Forecast evolution of substation CT-0947 during maintenance.....	127
Figure 75. Forecast evolution of substation CT-0944 during maintenance.....	127
Figure 76. ETER GUI, forecast tab. CT-0112.	130
Figure 77. ETER GUI, scenario switch closure. CT-0112.....	130
Figure 78. ETER GUI, scenario update with new changes. CT-0112.	131
Figure 79. ETER GUI, N-1 Contingency Analysis module. CT-0112.	131
Figure 80. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0112.....	132
Figure 81. Forecast evolution of substation CT-0113 during maintenance.....	132
Figure 82. Forecast evolution of substation CT-0114 during maintenance.....	132

List of Tables

Table 1. Key Outcomes	12
Table 2. Main characteristics of REE's grid.	20
Table 3. Summary of test conditions and test results for the AI agent	23
Table 4. Test case 1 for UC Ib01.....	25
Table 5. Key Performance Indicator 1 for Use Case Ib01.....	29
Table 6. Key Performance Indicator 2 for Use Case Ib01.....	30
Table 7. Test case 1 for UC Ib02.....	30
Table 8. Test case 2 for UC Ib02.....	34
Table 9. Test case 1 for UC Ib03.....	37
Table 10. Key Performance Indicator 1 for Use Case Ib02.....	42
Table 11. Key Performance Indicator 2 for Use Case Ib02.....	42
Table 12. Test case 1 in Cuerva's grid	50
Table 13. Key Performance Indicator 1 for Cuerva's use case	52
Table 14. Key Performance Indicator 2 for Cuerva's use case	53
Table 15. Key Performance Indicator 3 for Cuerva's use case	53
Table 16. Key Performance Indicator 4 for Cuerva's use case	54
Table 17. Key Performance Indicator 5 for Cuerva's use case	55
Table 18. Key Performance Indicator 6 for Cuerva's use case	56
Table 19. Test case 1 for UC Ib05.....	59
Table 20. Key Performance Indicator 1 for UC Ib05	62
Table 21. Test case 1 for UC Ib06.....	62
Table 22. Test case 2 for UC Ib06.....	67
Table 23. Key Performance Indicator 1 for UC Ib06	70
Table 24. Test case 1 for UC Ib07.....	71
Table 25. Test case 1 for UC Ib14.....	77
Table 26. Selected participants.....	82
Table 27. Executed transactions during for the validation of the DSO's DT as use case enabler in UC Ib14	82
Table 28. Key Performance Indicator 1 for UC Ib14	93
Table 29. Key Performance Indicator 1 for UC Ib14	94
Table 30. Suitability of dynamical downscaling for each renewable energy-relevant meteorological variable.....	101

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Table 31. Suitability of statistical downscaling for each renewable energy-relevant meteorological variable.....	101
Table 32. Suitability of machine learning downscaling for each renewable energy-relevant meteorological variable.	102
Table 33. Suitability of Hybrid approaches to downscaling for each renewable energy-relevant meteorological variable.	103
Table 34. Comparison of downscaling techniques on renewable energy criteria.....	104
Table 35. Test case 2 for UC Ib07.....	108
Table 36. Test case 3 for UC Ib07.....	113
Table 37. Test case 4 for UC Ib07.....	118
Table 38. Test case 5 for UC Ib07.....	123
Table 39. Test case 6 for UC Ib07.....	128
Table 40. Key Performance Indicator 1 for UC Ib07	133

List of Abbreviations and Acronyms

Acronym	Meaning
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
BPLC	Broadband Power Line Communication
DCU	Data Concentrator Unit
DER	Distributed Energy Resources
DSO	Distribution System Operator
DT	Digital Twin
EV	Electric vehicle
FPI	Fault Passage Indicators
IED	Intelligent Electronic Device
LFM	Local Flexibility Market
LFMO	Local Flexibility Market Operator
LTE	Long-term evolution
MV	Medium Voltage
NEMO	Nominated Electricity Market Operators
PLC	Power Line Communication
PV	Photovoltaic
RES	Renewable Energy Sources
RT	Real Time
RTU	Remote Terminal Unit
SCADA	Supervisory Control and Data Acquisition
TSO	Transmission System Operator
UC	Use case
WP	Work Package

Executive Summary

This work summarises the progress achieved in the TwinEU Digital Twin demonstrations for transmission and distribution grids, covering the REE, Cuerva and ANELL environments. Across these pilots, the work shows that Digital Twins can evolve from isolated modelling tools into operational decision-support layers that combine grid models, field data, forecasting, optimisation, simulation and, where relevant, federation mechanisms. The main contribution is the validation of how these capabilities can support system operators in addressing increasingly dynamic challenges linked to renewable integration, electrification, congestion management, grid resilience and planning under uncertainty.

For REE's transmission-grid Digital Twin, the work has demonstrated the value of using simulation tools for AI-based operational support and scenario generation of renewable resources for planning studies. The AI Agent use case shows that a Digital Twin can help operators detect critical operating conditions, assess the network state and identify remedial actions in a more systematic and traceable way. This contributes to faster operational analysis and supports assisted decision-making in the control centre. In parallel, the synthetic renewable-resource and climate-series generator demonstrates that Digital Twin tools can enrich planning studies by producing coherent meteorological and renewable-resource scenarios aligned with user-defined needs. Together, these results show that the REE Digital Twin contributes both to short-term operational awareness and to longer-term planning robustness in a system increasingly shaped by variable renewable generation.

For Cuerva's distribution-grid Digital Twin, the work has established a common methodological backbone for two complementary applications: long-term flexibility in medium-voltage networks and flexible connection schemes, with electric vehicle integration as a representative case. The key result is the definition of a data-driven segmentation framework that translates historical grid behaviour into stable operating states and time-dependent capacity blocks. This allows the DSO to distinguish between genuinely constrained periods and periods where unused grid capacity can be safely released. The contribution is therefore analytical as well as operational: the Digital Twin provides a basis for deciding when flexibility can be activated, when flexible connection capacity can be offered, and under which conditions these mechanisms remain technically safe, contractually usable and manageable for the operator.

For ANELL's distribution-grid Digital Twin, the work has provided operational evidence of how simulation, forecasting and real network data can support resilience assessment, hosting capacity analysis, maintenance planning and flexible connection preparation. The N-1 contingency analysis confirms the usefulness of the Digital Twin for identifying whether the grid remains secure under alternative operating configurations and for distinguishing between vulnerable and robust situations. The hosting capacity studies show that integration margins for renewable generation and demand can be assessed through grid-specific simulations rather than static generic assumptions, providing a more realistic basis for connection and reinforcement decisions. The maintenance-planning use case further demonstrates how forecasts, scenario simulation and security analysis can be combined to evaluate planned outages before execution and to support monitoring during the works. Overall, the document shows that the REE, Cuerva and ANELL Digital Twins address complementary needs across the electricity system: control-centre support and planning at transmission level, flexibility-based capacity management in distribution grids, and operational resilience, hosting capacity and maintenance support in active distribution networks. The work confirms the practical value of federated Digital Twin approaches while also highlighting that further validation, stronger interoperability and longer real-world operation will be needed to consolidate these services for full-scale deployment.

Key outcomes at a glance

Table 1. Key Outcomes

Pilot	Use Case	Evidence type	Main KPI	Result
REE	UC-Ib01. AI Agent for probabilistic grid status forecast and remedial actions identification for the TSO's Control Center Operator	Simulation in test network	Ib01-KPI1. Contingencies Resolution Rate	100% of the contingencies are identified and 71.43 % of the contingencies are solved
REE	UC-Ib02. DT for generation of synthetic series of renewable resources	Historical data	Ib02-KPI1. Time to Data Availability	2.3 seconds
Anell	UC-Ib05. DT-based N-1 contingency analysis	Simulation in a real network	Ib05-KPI. Critical elements identified	0, No critical elements are identified by the DT under normal operating conditions. The grid is N-1 contingent.
Anell	UC-Ib06. DT-enabled new RES integration validated plan in the MV grid	Simulation in a real network	Ib06-KPI1. Available bidirectional (RES and loads) power hosting capacity	~50MW (RES Hosting Capacity) and ~65 MW (Load Hosting Capacity), depending on the test case
Anell	UC-Ib07. DT-based grid maintenance planning activities	Real grid operation	Ib07-KPI1. Accuracy in recalculated power flows.	Average MAPE (Mean Absolute Percentage Error) of 10.89%
Cuerva	UC-Ib08. Long term flexibility in MV	Historical data	Ib08-KPI3. Operational complexity	5, within the compliance range of [3,7]
Cuerva	UC-Ib09. Flex Connections	Historical data	Ib08-KPI3. Operational complexity	5, within the compliance range of [3,7]
Anell	UC-Ib14. Local Flexibility Market-enabled Flexible Connection Agreements	Simulation in a real network	Ib14-KPI2. Increased bidirectional (RES and loads) power hosting capacity.	3.51 MWh

1 Introduction

1.1 Objectives

The objective of Deliverable D8.2 is to describe the methodology and testing results of digital twin-enabled use cases across selected transmission and distribution grids. These use cases aim to improve decision-making processes, enhance network planning, and support real-time operations through predictive analytics, simulation tools, and data federation techniques. The deliverable builds on work done in earlier stages of WP8. These efforts are in line with the European Union's strategic vision for low-carbon energy future as outlined in the Energy Roadmap 2050 [1], REPowerEU [2] and Fit for 55 [3] plans.

1.2 Structure of the document

The document is divided into the following sections:

- Section 2 presents the main use cases developed in TwinEU, detailing their goals, implementation strategies, and the operational or planning gaps they address.
- Section 3 outlines the methodology applied to each pilot site (REE, Cuerva, and ANELL), including the description of their grids, use case relevance, and approaches to implementation and testing.
- Section 4 provides concluding remarks and identifies limitations and lessons learned, before outlining recommendations for future work.

2 TwinEU's contribution to digital twin applications

Grid operation and planning

2.1 AI Agent for Grid State Forecasting and Remedial Action Identification

This use case addresses one relevant challenge faced by the transmission system operator, particularly the growing complexity of real-time grid management due to increased renewable energy penetration. The proposed digital twin will integrate artificial intelligence to enhance situational awareness and decision-making in the control centre.

At present, system operators must monitor and respond to rapidly changing conditions in the power system under increased complex scenarios with high penetration of renewable energy. Short-term operational scenarios should be detected and real-time remedial actions for power system operation evaluated and implemented. The AI-based module will fill this gap by identifying potential operational risks ahead of time and by suggesting preventive or corrective actions, helping operators maintain system security with greater precision.

By analysing data monitored from the power system, the tool can anticipate scenarios that may compromise reliability and recommend effective remedial interventions to mitigate those scenarios. If working well, this can provide extended capabilities to operators during critical situations for faster and effective reaction.

Operational gaps addressed:

- Difficulty in managing variability from renewable sources.
- Need for faster, more reliable decision-making in control centre under increase complexity and uncertainty.

2.2 DT for generation of synthetic series of renewable resources

Today, the planning process depends on a narrow set of historical weather and generation data, limiting the diversity and accuracy of scenarios simulated and considered in the network design. This use case focuses on supporting long-term grid planning by generating realistic, diverse synthetic renewable resource profiles adapted to different possible future scenarios.

The proposed digital twin tool will allow the generation of wind and solar resource profiles that are statistically consistent with real-world conditions, yet flexible enough to explore different hypotheses and future scenarios. This enables system planners to better assess how the power transmission grid should be robustly designed under diverse conditions, including unusual patterns of renewable availability.

Importantly, the tool ensures temporal and spatial correlation across the generated data series, making them suitable for use in integrated planning studies.

Planning and forecasting gaps addressed:

- Dependence on limited historical datasets for resource simulation.
- Inability to test a wide range of future scenarios.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

- Lack of high-resolution, correlated renewable resource data.
- Need for improved input data for operational forecasting models.

2.3 DT-based N-1 contingency analysis

The DSO needs to be able to assess the grid response under different boundary conditions, and this need starts with identifying the critical elements in the grid to validate that an eventual failure would not imply the disruption of the system.

The DT-based N-1 contingency analysis use case is aimed at valorising the RT simulation capacities of the modelled distribution grid DT to assess the grid resilience by matching SCADA data and the power flow optimization simulation results. The objective of this use case is to analyse the security and stability of the distribution networks under different scenarios and operating conditions, identifying bottlenecks and critical points in the system towards grid development and reinforcement planning.

The Digital Twin is provided with the grid topology model and the measurements for all the feeders (historical and RT data). The objective is to understand whether the grid is capable of supporting the generation and consumption loads at any time under different boundary conditions, preventing the grid from collapsing.

First, an optimal power flow is performed over the grid under normal conditions to check the network stability. Then, using a list of critical elements of the network such as lines or transformers, among others, a simulation is started by disconnecting each critical element one by one, checking the stability of the network again without that element, by means of a power flow.

Therefore, this use case will determine whether the network is N-1 contingent, in case all tests are passed successfully, or not contingent, in case one of the tests fails. In this last case a specific report will be generated identifying the critical elements and the conditions under which these elements are critical.

2.4 DT-enabled new RES integration validated plan in the MV grid

Distributed Energy Resources deployment is spreading across the territory, tensioning the operation of Distribution Networks and making them more complex to balance. DSOs need to have an up-to-date simulation tool to understand the effect of further distributed RES plants deployment in their network's premises, as well as the capacity limits of critical nodes with new installations requests so that permits are only given if the future situation does not create issues in the grid. For such purposes, an automatised smart service based on the Digital Twin of the grid will be able to identify critical scenarios on its own without excessive manual configuration of the DSO personnel.

This Use Case proposes a specific collaboration between the DT of the distribution system and the digital behavioural model of the RES power plants for the integration assessment in different nodes of the grid. The result of the Use Case will be a viability assessment for further deployment of RES systems in critical areas of the grid, which will contribute to the grid planning activities.

TwinEU leverages the implementation of Digital Twins for the uptake, in terms of grid capacity planning, of distribution companies by analysing the impact that newly deployed commercial and utility-scale renewable power plants will have in their networks.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

The software tool that embeds ANELL's DT, ETRA's ÉTER, includes the generation of time series of data able to replicate the behaviour of a renewable power plant (focused on PV but different types could be considered if it is of interest) and simulates, supported on the grid models hosted by ANELL, the dynamic behaviour of the grid during a relevant period of time (period to be defined). During this simulation, the DT will analyse the evolution of the grid based on multiple input parameters and forecasts, identifying critical points and situations that may derive from such RES connections. Additionally, ÉTER enables the simulation of multiple combinations of scenarios of different power plants connected simultaneously, identifying the unfeasible combinations and their bottlenecks.

The results of these analyses will be used by ANELL for grid planning purposes for the short, medium and long terms.

2.5 DT-based grid maintenance planning activities

The electricity distribution business is gaining responsibilities from the classic power delivery of bulk generation to end-users towards managing highly complex systems with non-dispatchable generation units, flexible assets, conventional consumers and a rapidly changing environment with more and more RES power deployed each year and new business models currently being sandbox-tested such as local flexibility markets.

This increase in complexity generates the need for higher visibility over the network and smoother planning when it comes to maintenance works that may jeopardise the normal power supply.

Answering this need, TwinEU leverages the implementation of Digital Twins in order to, first, plan the maintenance works in a way that optimises the security of supply to the maximum extent and then, validate in real-time that the forecasted grid evolution is indeed going as expected.

For the planning of the maintenance works, the systems run the power flow and estate estimation algorithms to identify eventual issues that may arise in the network during the period of time in which the activity will be ongoing. This will allow the DSO to plan a schedule with minimum impact on the power supply. For the real-time operation, the algorithms are constantly receiving RT data to recalculate the values and verify the correct functioning of the system.

2.6 Long term flexibility in MV

The integration of distributed energy resources, renewable generation, and electrified demand is progressively increasing the operational complexity of medium-voltage (MV) distribution networks. In this context, TwinEU examines how digital twin technologies combined with flexibility orchestration can support DSOs in three interconnected dimensions: control centre decision-making, resolution of technical restrictions such as congestion, and long-term operational planning.

Digital Twin Contribution to Control Centre Support

The Cuerva digital twin provides control centre operators with an updated representation of the MV network, integrating real-time measurements, operational topology, and short-term forecasts of load demand and distributed generation. This enhanced situational awareness enables operators to anticipate critical network states before they materialize, moving from a reactive to a proactive operational paradigm.

Rather than responding to congestion events after their occurrence, operators can access predictive alerts and pre-evaluated corrective actions directly through the digital twin platform. This

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

capability reduces decision time and supports more informed, data-driven interventions at the control centre level.

Technical Restriction Resolution Through Flexibility

A central analytical contribution of this use case is the evaluation of flexibility services as an alternative mechanism for resolving technical restrictions that would traditionally require physical grid reinforcement.

The digital twin enables the assessment of flexibility availability from controllable loads and distributed energy resources, and the simulation of different activation strategies under constrained network conditions. Through this analytical framework, TwinEU quantifies the extent to which demand response, load shifting, and DER management can effectively resolve congestion without infrastructure investment, providing DSOs with a validated methodology for flexibility-based restriction resolution.

Long-Term Operational Planning

Beyond real-time operation, the digital twin supports planning activities by enabling the simulation of future network scenarios under varying assumptions of renewable penetration, demand growth, and electrification rates. This allows the DSO to evaluate which congestion situations can be durably resolved through flexibility mechanisms and which may ultimately require conventional reinforcement.

The use case thus contributes an analytical framework for investment deferral assessment, providing a structured basis for comparing flexibility-driven operation against capital-intensive grid upgrades. Key performance dimensions include reduction in congestion events, flexibility utilization rates, improvement in asset utilization, and the estimated reduction in reinforcement investment requirements under different planning horizons.

2.7 Flexible EV Connections

The accelerating deployment of electric vehicle (EV) charging infrastructure introduces new and dynamic demand patterns in medium and low-voltage (MV/LV) distribution networks. Concentrated EV charging can cause voltage deviations, feeder overloads, and a reduction in available hosting capacity challenges that, if unaddressed, would require significant conventional reinforcement. This use case examines how the Cuerva digital twin, combined with smart charging coordination, contributes to control centre support, technical restriction resolution, and network planning in high-electrification scenarios.

Digital Twin Contribution to Control Centre Support

The digital twin integrates monitoring of EV charging demand alongside broader network measurements, offering control centre operators a real-time view of the combined impact of electromobility on grid conditions.

This visibility transforms EV infrastructure from an uncontrolled variable into a monitorable and manageable element within the control centre's operational picture.

Technical Restriction Resolution Through Smart Charging

The primary analytical focus of this use case is the evaluation of flexible EV charging as a mechanism for resolving voltage and capacity restrictions in MV and LV feeders without resorting to infrastructure upgrades. The digital twin platform simulates the impact of different charging profiles and penetration levels and evaluates the effectiveness of flexibility strategies such as charging power limitation, demand rescheduling, and adaptive charging coordination.

Through this analysis, TwinEU assesses the degree to which smart charging flexibility can maintain acceptable voltage profiles and avoid thermal overloads under realistic high-EV scenarios, providing a technically grounded alternative to conventional reinforcement approaches such as transformer upgrades or feeder extensions.

Operational Planning for EV Integration

At the planning level, the digital twin enables the systematic evaluation of EV hosting capacity under different infrastructure and flexibility configurations. By simulating future penetration scenarios, the DSO can determine the conditions under which flexible connection schemes are sufficient to maintain grid stability and identify the thresholds beyond which physical reinforcement becomes necessary.

This analytical capability supports evidence-based planning decisions, allowing DSOs to maximize the use of existing network assets while managing the risks associated with large-scale electrification of transport. Performance evaluation focuses on voltage quality improvement, load balancing efficiency, hosting capacity increase, and the reduction of reinforcement requirements attributable to flexibility activation.

2.8 DT-Enables Flexible Connections through Local Flexibility Markets

Highly industry-populated areas are experiencing an increase in the use of electricity both at demand side (electrification of industrial processes towards meeting sustainability goals) and at generation side (deployment of PV self-consumption installations covering the maximum available roof).

In this context, the classic methodology for calculating the available capacity at a specific node is obsolete, as it does not take into account the dynamic component that parametrizes the evolution of the grid use (power flows and congestion) over the year, but rather it obtains results based on a fixed percentage of the maximum demand.

TwinEU leverages the implementation of Digital Twins for the uptake, in terms of grid capacity planning, of distribution companies by analysing the impact that newly deployed commercial and utility-scale renewable power plants will have in their networks.

When a PV installation connection point request is received, the DSO's DT makes a series of scenario simulations to identify bottlenecks where the grid gets congested. Among the results of these simulations, the DSO will get the maximum power for which no congestions are generated in the grid at any time. This will be the base power granted for the plant. From there onwards, in increased power steps, additional results will be given stating, for each step, an estimation for the hours of the year that the flexible connection point could be increased to that export peak power. This way, the developer could choose, based on non-binding estimation, to what extent is profitable for them to

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

deploy more power. This increased power granted can be due to the lack of a congestion or the establishment of a long-term local flexibility market. For such periods of time, the DSO's DT communicates with the NEMO's LFM's DT in order to open a session in the market for flexibility provision. Once the offers have been received (estimated based on the registered assets for the selected zones of the grid) and the market has been cleared, the DSO's DT runs once again the set of eventual scenarios to verify that all the power can be injected into the grid without causing further congestions. Once the grid status has been verified as suitable, the DSO increases the connection power capacity for the specific period of time where no congestions are generated.

3 Methodological approach for the implementation of the DT Federation-enabled Use Cases

3.1 REE's transmission grid

3.1.1 Overview of REE's Transmission Grid

Red Eléctrica (REE) operates and manages the high-voltage transmission grid of the Spanish electricity system. The grid covers the entirety of mainland Spain and includes interconnections with neighbouring countries such as Portugal, France, and Morocco. With thousands of kilometres of high-voltage lines (220 kV and above), hundreds of substations, and multiple cross-border links, REE's infrastructure forms the backbone of electricity transmission across the country.

Table 2. Main characteristics of REE's grid.

Variable	Value	
Transmission lines 400kV, 200kV (km)	46,155.2847	
Substations	>700 substations, >6,000 positions, >225 transformers	
Transformation capacity (GVA)	99.1	
Interconnections exchange capacity (GW)	France (2.8) Portugal (4.2 ES-PT and 3.5 PT-ES), Morocco (0.9 ES-MC and 0.6 MC-ES) Andorra (0.1)	
All-time peak electricity demand (GW)	45.45	
Installed Power Capacity (GW)	Renewable	95.6 (~41.6 Solar and ~33.2 Wind)
	Non-Renewable	43.49 (~26.2 CCGT, ~7.1 Nuclear)
	Storage	3.43 (~3.3 Pumped Hydro, ~0.01 utility-scale batteries)
	Total	142.56

The Spanish transmission grid is characterised by a relevant increase of renewable power generation, especially wind and solar, geographically distributed over the country and often located far from major consumption centres. Additionally, the high penetration of variable renewable generation has introduced significant challenge for system planning and operation, including increased uncertainty in renewable resources, power flows and congestion risks and stability.

As a Transmission System Operator (TSO), REE is responsible for ensuring the reliability and security of supply of Spanish power system, maintaining system balance and facilitating the integration of new energy sources. These tasks require sophisticated planning tools, real-time monitoring capabilities, and predictive systems that support decision-making under uncertainty, especially given the evolving energy mix and the decarbonization targets set at national and European levels.

As a Transmission System Operator (TSO), REE is responsible for ensuring the reliability and security of supply in real time, maintaining system frequency, coordinating maintenance, and facilitating the integration of new energy sources. These tasks require sophisticated planning tools, real-time monitoring capabilities, and predictive systems that support decision-making under uncertainty—especially given the evolving energy mix and the decarbonization targets set at national and European levels.

To address these challenges, the deployment of digital twin technologies and AI-based prescriptive and generative systems with advanced functionalities is regarded as a step toward reinforcing REE's

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

operational capabilities. These innovations will help ensure grid security and efficiency in increasingly complex and renewable-dominated scenarios.

3.1.2 Use Cases Related to REE

Two digital twin-based use cases have been developed to address specific operational and planning challenges faced by REE in the context of Spain's transmission grid. Both use cases leverage REE's historical data and operational expertise to enhance the management of an increasingly complex power system with high renewable penetration.

The use cases related to REE are:

- **UC-Ib01:** AI Agent for probabilistic grid status forecast and remedial actions identification for the TSO's Control
- **UC-Ib02:** Digital Twin for generation of synthetic series of renewable resources

The first use case, AI Agent for remedial actions identification for the TSO's Control Centre Operator, is focused on supporting real-time operation of the transmission system by identifying voltage constraint in the network and proposing actions to control centre operators for mitigation those voltage constraints. By combining artificial intelligence with optimization algorithms, the system processes real-time grid data to calculate optimal operating strategy under critical voltage violation and determines the most effective corrective actions.

The second use case focuses on increased grid planning robustness through the generation of synthetic time series for renewable resource like wind and solar. The tool developed in this use case generates synthetic renewable resources series (wind speed, solar radiation, precipitation, etc) that are incorporated as input in the planning process under different scenarios. These time series preserve both temporal and spatial correlations and can be tailored to represent various climatological scenarios, thus supporting long-term planning and resilience analysis.

Together, these use cases support REE in achieving higher operational efficiency, resilience, and strategic planning accuracy in line with national and European energy transition targets.

3.1.3 Methodology for Implementation

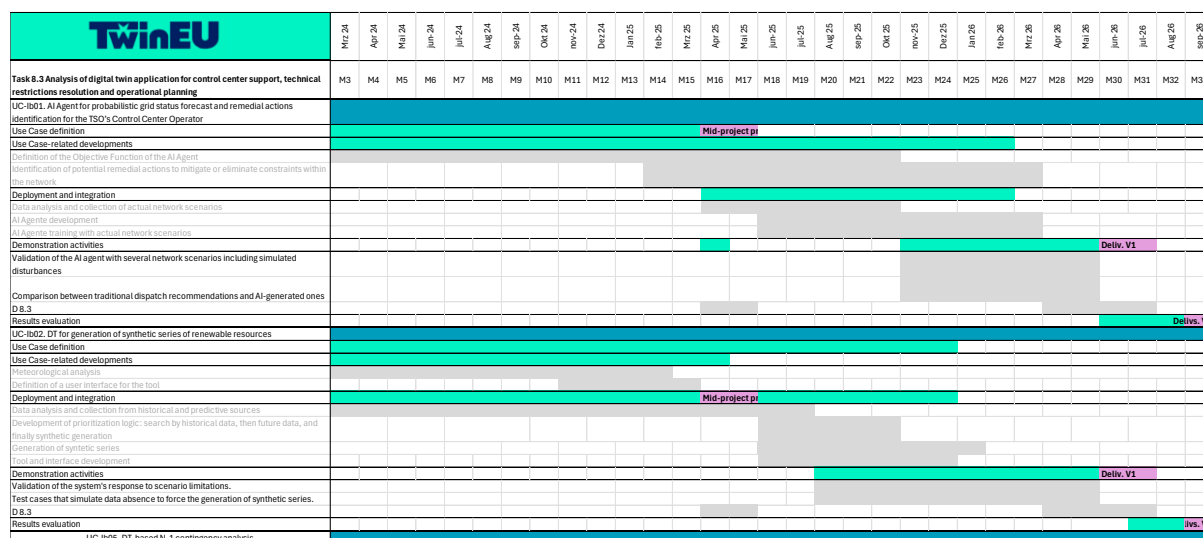


Figure 1. Transmission Grid Digital Twin use cases planning developed by REE and CIRCE

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

The above Gantt chart (Figure 1) shows the activities and planning associated to the transmission grid use cases control centre decision-support and network planning renewable resource series (UC-IB01 and UC-IB02).

3.1.3.1 UC Ib01: AI tool decision-support for control centre

The proposed AI-based decision-support agent continuously receives the current operating state of the transmission network through standard power system data files (*.raw* or *.m*), containing detailed information on network topology, generation units, loads, transmission assets, and electrical variables such as voltage magnitude, voltage angle, active power, reactive power, and frequency. The overall workflow of the proposed framework is illustrated in Figure 2, which presents the sequence of data acquisition, processing, analysis, and decision-support stages.

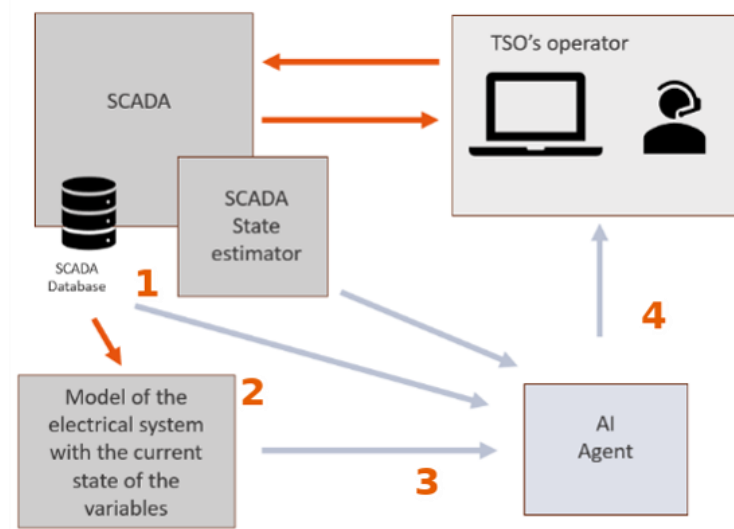


Figure 2. Flowchart AI Agent.

The methodology implemented within the Digital Twin framework follows a four-stage decision support pipeline:

- 1) Data acquisition and network model preparation
- 2) Fast network state assessment through Extended DC Power Flow (EDCPF).
- 3) Constraint detection and operating condition analysis.
- 4) AI-assisted remedial action recommendation and validation.

Step 1: Training Dataset Generation and Preparation

For the voltage-control application, the AI models have been trained and validated using a dedicated dataset of [4] [5] [6] [7] [8] AC power flow scenarios generated from the IEEE 118-bus transmission system [13]. The dataset includes a wide range of operating conditions obtained through randomized variations of load levels, generator voltage setpoints, transformer tap positions, shunt statuses, and transmission line outages, including N-1 and selected N-2 contingency situations. The generated scenarios cover voltage magnitudes ranging from 0.84 pu to 1.14 pu and comprise operating conditions with up to 15 buses experiencing voltage violations. The resulting dataset provides a representative set of voltage-security conditions for training and validating the AI-based decision-support agent.

Step 2: Network State Assessment

Using the Extended DC Power Flow (EDCPF) model [10], the agent performs a fast assessment of the network operating condition, estimating both power flows and voltage magnitudes while maintaining the computational efficiency required for real-time applications. The resulting system state is automatically evaluated against operational and regulatory limits, including voltage constraints, thermal loading limits, power transfer capabilities, and security criteria.

Step 3: Constraint Detection and System Analysis

The AI agent observes a comprehensive representation of the network state, including bus voltage magnitudes and angles, reactive power generation, transformer tap positions, shunt statuses, branch loading levels and network topology information, allowing a detailed characterization of the current operating condition. Based on this representation, the agent identifies voltage violations, network congestions and other operating conditions requiring corrective intervention.

Step 4: AI-Based Remedial Action Recommendation

Whenever abnormal operating conditions, network congestions, voltage violations, or potential security risks are detected, the agent evaluates candidate remedial actions through an Optimal Power Flow (OPF) framework. The optimization process identifies the most cost-effective control strategy while ensuring compliance with all operational constraints and maintaining system security.

For voltage-control tasks, a Deep Reinforcement Learning (DRL) prescriptive agent based on the Soft Actor-Critic (SAC) algorithm has been developed to determine coordinated corrective actions, including generator voltage reference adjustments, transformer tap changes and shunt switching operations. The agent was trained using a dedicated dataset of 20,000 AC power flow scenarios representing a broad range of voltage-security conditions.

Once trained, the resulting neural-network policy can analyse previously unseen operating conditions and provide near real-time recommendations for voltage control. Evaluation on 500 unseen scenarios demonstrated a successful mitigation of voltage violations in 91.8% of the test cases, requiring on average only 2.09 control actions per scenario while maintaining a 0% non-convergence rate.

Table 3. Summary of test conditions and test results for the AI agent

Item	Description
Power system model	IEEE 118-bus transmission network
Training dataset	20,000 AC power flow scenarios
Learning approach	Hybrid DRL (Soft Actor-Critic)
Control variables	Generator voltage setpoints, transformer taps, shunts
Validation dataset	500 unseen scenarios
Success rate	91.8 %
Average actions required	2.09
Non-convergence rate	0 %

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

The proposed solution provides operators with fast, reliable, and actionable recommendations that enhance situational awareness, reduce response times, and improve overall system security and operational efficiency.

3.1.3.2 UC Ib02: : Synthetic renewable generation series for network planning

The developed digital twin tool for this use case enables the generation of synthetic multivariate climate scenarios over the Iberian Peninsula through advanced artificial intelligence and multi-objective optimization techniques. Its main purpose is to provide physically consistent meteorological scenarios that can be used as inputs for energy system planning, renewable integration studies, and power network assessment activities.

The solution is built upon a 3D U-Net architecture enhanced with a Variational Autoencoder (VAE) [16] bottleneck and Feature-wise Linear Modulation (FiLM) [17] conditioning mechanisms. This architecture learns a probabilistic latent representation of meteorological fields comprising temperature, wind speed, and solar irradiance while preserving the spatial and temporal dependencies inherent in historical climate datasets. The model operates on spatial-temporal tensors generated from pre-processed and normalized meteorological observations and climate projections. Figure 3 illustrates the overall workflow of the developed tool, from the required input data to the final generated outputs

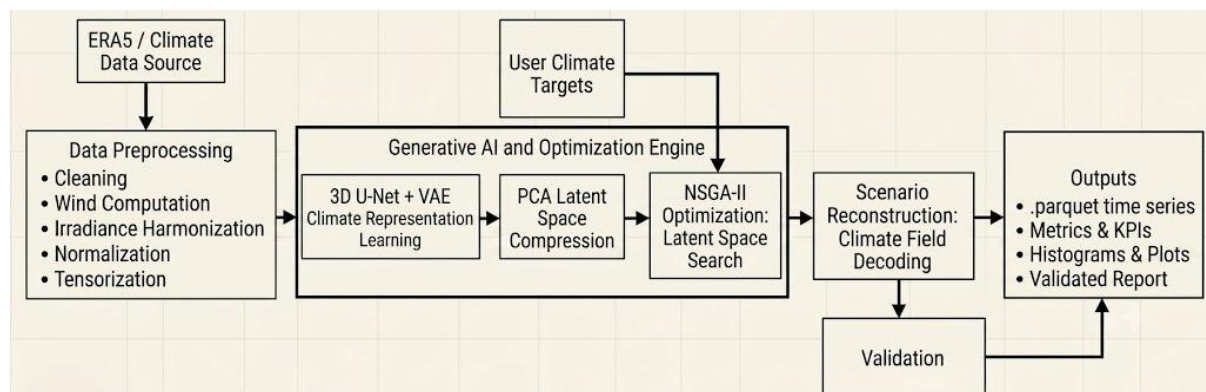


Figure 3. Flowchart synthetic series generator

Once trained, the latent representation is reduced using Principal Component Analysis (PCA), enabling an efficient exploration of the latent space. A Non-dominated Sorting Genetic Algorithm II (NSGA-II) [18] is then applied to generate new climate scenarios that satisfy user-defined physical targets, such as desired average temperature, wind speed, or irradiance values, while maintaining the climatological coherence learned during training.

The generated scenarios undergo physical plausibility validation and visualization procedures before being exported for downstream applications. The tool therefore acts as an intermediate layer between climate datasets and energy planning models, allowing the generation of realistic, controllable, and reusable climate scenarios tailored to specific operational or planning requirements.

The best-performing latent solution is decoded into a complete spatial-temporal climate field, validated for physical plausibility, and exported as a synthetic climate time series in Parquet format.

The validation was performed through three distinct test cases, each corresponding to one of the solution-generation approaches supported by the tool: identification of the most suitable historical data series, selection of a forecasted future data series, and generation of a synthetic data series matching the specified target conditions.

3.1.4 Testing Scenarios and Performance Metrics

Both digital twin tools described in previous section - the AI-based operational agent and the synthetic time series generation tool - have been tested across various scenarios in order to evaluate their performance and the results obtained. The selected scenarios reflect really meaningful and representative circumstances.

3.1.4.1 UC Ib01: AI tool decision-support for control centre

The following tables summarize the test case conducted to validate the AI tool decision-support for control centre tool, together with the key performance indicators (KPIs) used to assess its effectiveness.

Table 4. Test case 1 for UC Ib01

Test Case ID	TC Ib01.1
Name	AI agent for automated voltage violation detection and mitigation using AC Power Flow and Optimal Power Flow -Volt-Var Optimization (OPF-VVO)
Related UC	UC Ib01
Timeframe	Simulation-based experiment.
Targets	Validate the capability of the AI agent to detect voltage violations, identify corrective actions and validate them through AC power flow calculations.
Actors involved	• CIRCE: development of AI agent and power system simulation environments. • REE (Spanish TSO): definition of technical requirements, knowledge and data sharing of system operation and results validation.
Assets and systems involved	• IEEE 118-bus transmission network model • Model import module: to import the network model and scenarios and properly process for AI agent preparation • EDCPF solver: DC power flow with extended voltage calculations. Conventional DC power flow • OPF/VVO module: AI-agent module for Optimal Power Flow resolution combined with Voltage Var optimization • JSON reporting module
Triggering Event	Detection of voltage magnitude violations (under/over voltage conditions) after executing an EDCPF on the network state contained in the .raw file.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Pre-condition	IEEE 118-bus network loaded from a valid .raw file. Initial operating condition modified to generate voltage violations.
Experiment description	An AC power flow is executed using the IEEE 118-bus system. The AI agent analyses the resulting operating state and identifies buses operating outside the admissible voltage range (0.95–1.05 pu). The mitigation engine applies corrective actions following a predefined priority order, starting with no-cost actions and progressing to optimization-based actions when necessary. After each action, a new EDCPF is executed to validate the impact. Once all violations are removed or no additional actions are available, the agent generates a JSON report containing the detected issues, corrective actions applied, and final network status.
Post-condition	Proposed recommendations for voltage mitigation and effect on the operational conditions of the power system. Operating state stored and reported in JSON format.
Datasets required for the experiment	IEEE 118-bus .raw network model, bus voltage limits, generator reactive power limits, transformer data, network topology data.
Field data to be gathered	Bus voltages, active and reactive power injections, line loadings, generator outputs, corrective actions applied, EDCPF power flow convergence results, execution time, number of iterations.
Related KPIs	Ib01-KPI1: Contingencies Resolution Rate. Ib01-KPI2: Contingency Analysis and Resolution Time
Results of the experiments	
1. Base Case Initialization: The network status is first solved using the Extended DC Optimal Power Flow (EDCPF) model to obtain a secure reference operating state, including power flows, voltage angles, and estimated voltage magnitudes. Different voltage violations at selected buses are introduced into the system. 2. Detection by the AI Agent: The AI agent monitors the network state and automatically identifies buses operating outside acceptable voltage limits (Minimum voltage = 0.95 pu. and Maximum voltage = 1.05 pu.)	

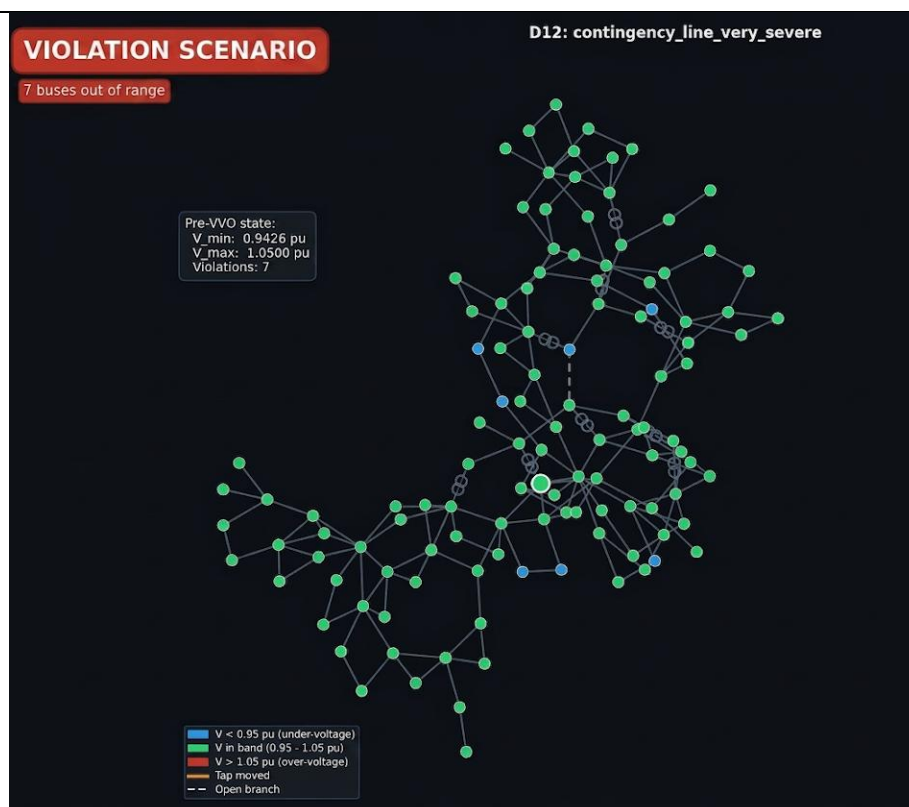


Figure 4. Initial state: 7 undervoltage violations detected.

3. Analysis and Recommendation: Using the Graph Neural Network (GNN)-based OPF model, the agent evaluates the network condition and determines the optimal corrective actions required to restore normal operation while minimizing operating costs.



Figure 5. AI Agent calculation

4. Application of Corrective Actions: The recommended actions, such as generation redispatch or network control adjustments, are applied to the EDCPF model.

5. Validation of Results: A new power flow calculation is performed to verify that voltage levels have returned within operational limits and that all network constraints are respected.

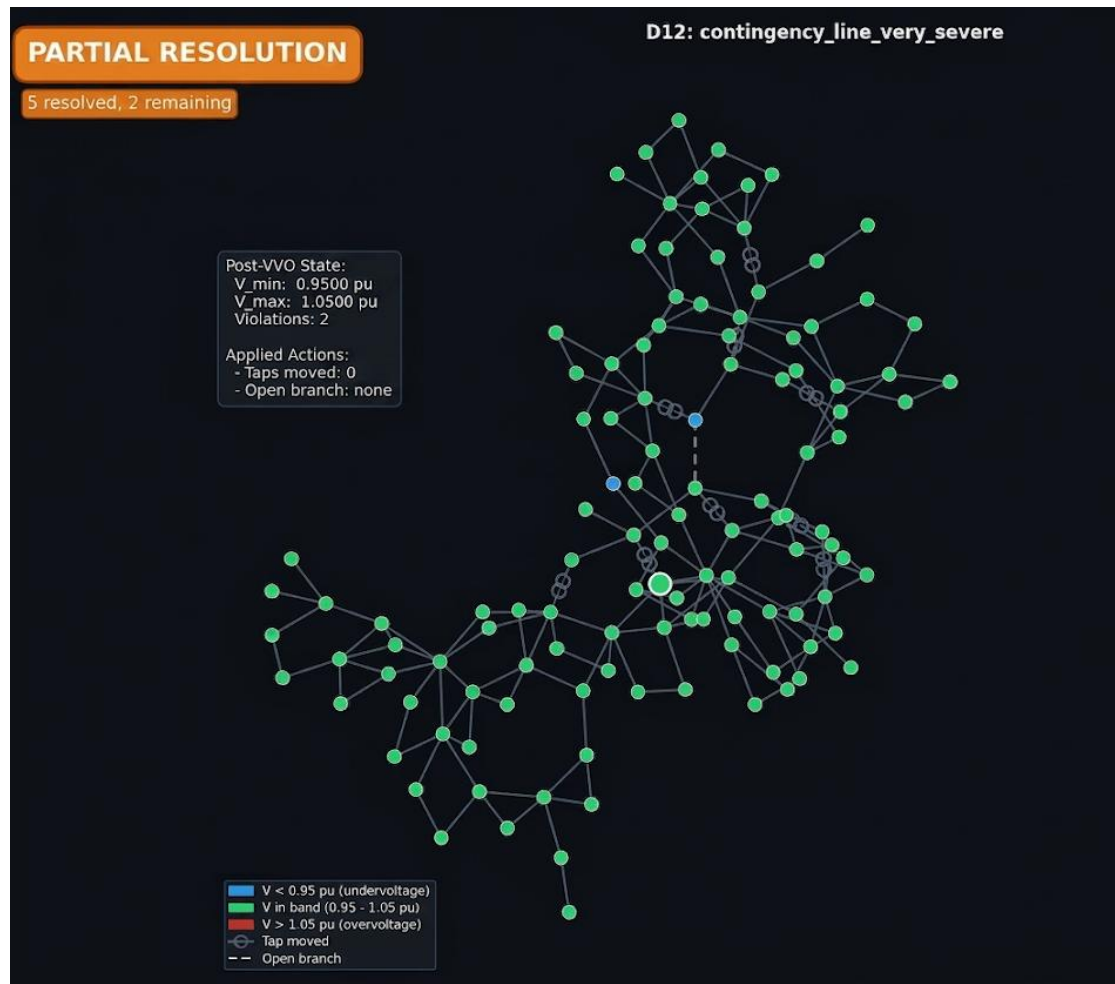


Figure 6. Final state: 2 undervoltage violations detected

The effectiveness of the AI agent is evaluated by measuring the percentage of voltage violations resolved, the quality of the recommendations, and the computation time required to reach a solution.

KPIs obtained:

- Ib01-KPI1: Contingencies Resolution Rate: 100% of the contingencies are identified and 71.43 % of the contingencies are solved based on the available remedial actions for voltage constraints (the other actions contingencies cannot be solved with the available remedial actions and other actions should be considered)
- Ib01-KPI2: Contingency Analysis resolution Time=30ms

Qualitative assessment of the results
The AI-assisted mitigation workflow significantly reduced the number of bus voltage violations while minimizing operational interventions. The selected corrective strategy relied exclusively on reactive power redispatch, avoiding more intrusive actions such as transformer tap modifications or network reconfiguration. The results demonstrate the effectiveness of the proposed approach for automated voltage control and decision support in transmission system operation.

Table 5. Key Performance Indicator 1 for Use Case Ib01

KPI ID	Ib01-KPI1
KPI Name	Contingencies Resolution Rate
Related Use Case	Ib01
KPI Description	Measures the percentage of contingencies successfully identified and resolved by the AI agent within a defined period.
KPI Formula	$\frac{\text{number of voltage – related incidents resolved}}{\text{total number of voltage – related incidents reported}} \times 100$
Variables explanation	<i>number of voltage-related incidents resolved</i> : Cases where the AI identified the root cause and provided a successful corrective action. <i>total number of voltage-related reported</i> : All voltage-related incidents received by the system during the measurement period.
Unit of measurement	Percentage (%)
Baseline	-
Reference signal(s)	N/A
Comments	Resolution can be validated through customer confirmation, restoration of voltage within acceptable limits, or closure by a human operator.

Table 6. Key Performance Indicator 2 for Use Case Ib01

KPI ID	Ib01-KPI2
KPI Name	Contingency Analysis and Resolution Time
Related Use Case	Ib01
KPI Description	Measures the time required by the AI agent to analyse a reported contingency, identify its root cause, and provide a recommended corrective action.
KPI Formula	N/A
Variables explanation	N/A
Unit of measurement	Seconds (s), milliseconds (s) or minutes(m)
Baseline	< 3 minutes
Reference signal(s)	N/A
Comments	Lower values indicate that the AI agent can analyse contingencies and provide corrective actions more quickly, demonstrating a higher level of readiness for real-time operational use.

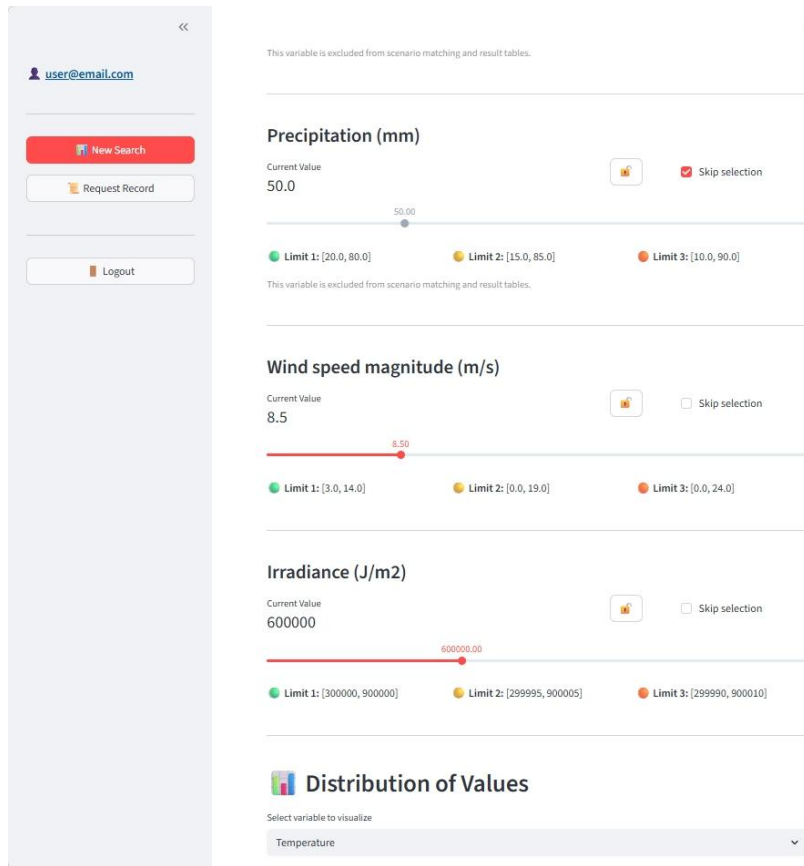
3.1.4.2 UC Ib02: Synthetic renewable generation series for network planning

The following tables present the test results and the evaluation metrics used to assess the proposed methodology for Use Case 2: Synthetic renewable generation series for network planning. The assessment considers both the time required for the generated or selected data to become available for use and the deviation between the obtained results and the expected target values.

Table 7. Test case 1 for UC Ib02

Test Case ID	TC Ib02.1
Name	Identification of a suitable historical Climate Scenarios through Pareto optimum for power system planning
Related UC	UC Ib02
Timeframe	Simulation-based experiment (offline validation).
Targets	Select a historical climate scenario with an average windspeed of 8.5 m/s and an average solar irradiance of 600,000 J/m ²
Actors involved	REE: technical requirements definition, knowledge and data, methodology co-definition and results validation.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

	CIRCE: development climate scenarios catalogue and selection algorithm.
Assets and systems involved	- ERA5 datasets. - Climate scenario selection algorithm - Validation and visualization modules
Triggering Event	User request for the selection of a historical value that matches a requested meteorological target.  Figure 7. Target Definition Interface - TC Ib02.1
Pre-condition	- Pareto weights configured. - Historical climate dataset available.
Experiment description	The user defined target values of 8.5 m/s for mean wind speed and 600,000 J/m² for mean irradiance. The catalogue of historical climate scenarios is parsed to find the closest historical scenario.
Post-condition	A historical multivariate climate time series has been selected, validated, and exported in Parquet format. When clicking the “Download” button, the user is redirected to downloading the file.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

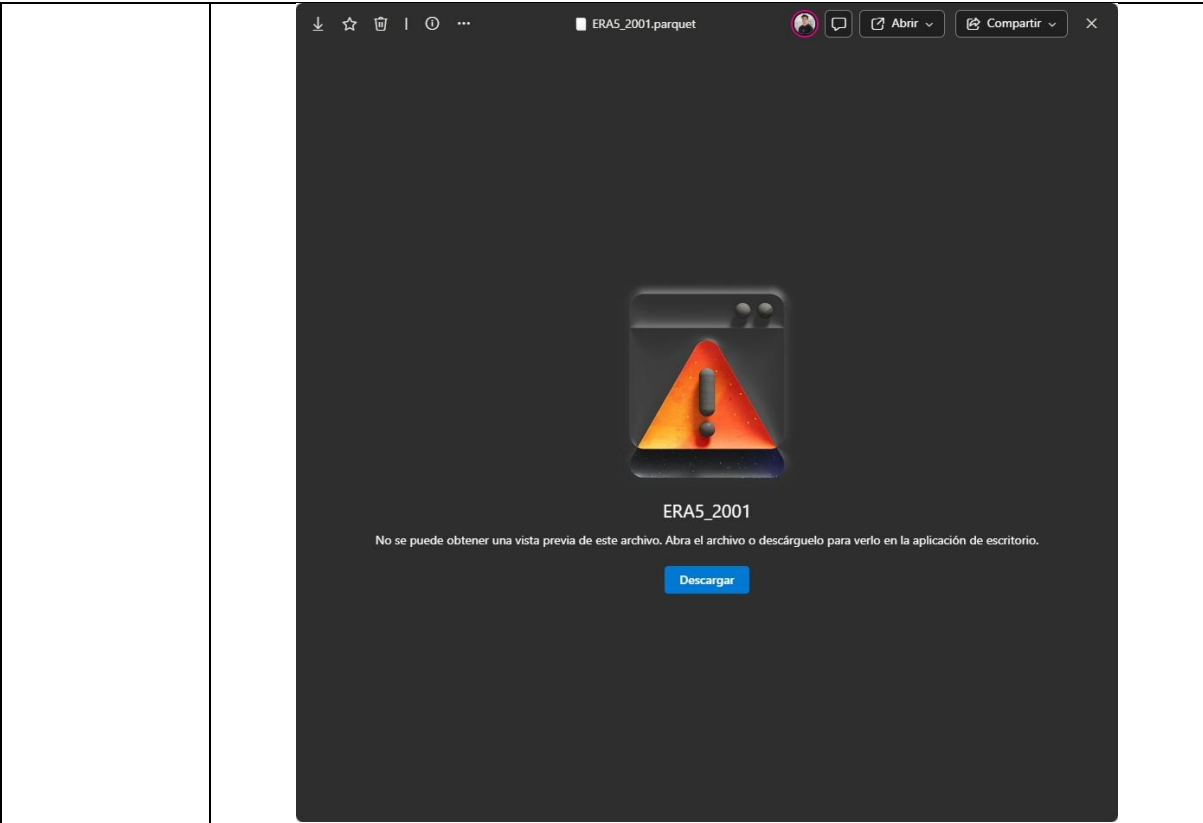


Figure 8. Data download interface

After downloading it, the scenario is visible for all other users, ensuring easy access to already-requested data (Figure 9)

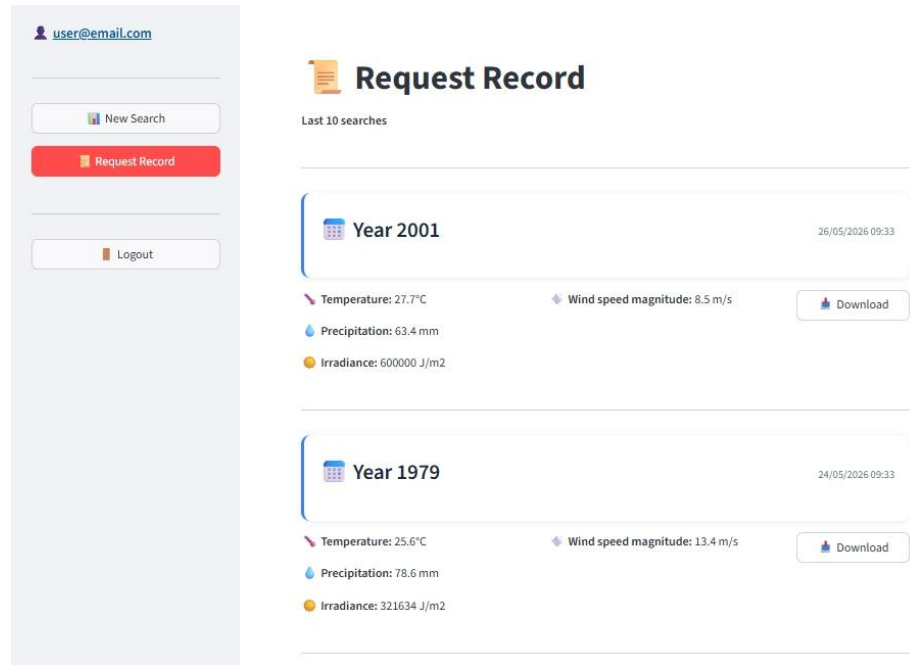


Figure 9. Request Record – TC Ib02.1

Datasets required	• ERA5 climate datasets • Historical statistical reference records
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D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

for the experiment	
Field data to be gathered	- Target values - Historical values - Manhattan distance to target.
Related KPIs	Ib02-KPI1: Time to Data Availability Ib02-KPI2: Expected Results Deviation

Results of the experiment

The resulting dataset was exported in Parquet format for subsequent power system analyses (Figure 10).

#	DateTime	#	Latitude	#	Longitude	#	Wind speed	#	Temperature	#	Precipitation	#	Irradiance	#	scenario	#	origin
0	2001-05-01 00:00:00		44.0		-10.0		4.5187725830078125		284.364990234375		0.0002374649478115525		0.0		0	ERAS	
1	2001-05-01 00:00:00		44.0		-9.75		4.2721710205078125		284.794833984375		0.00027084350589375		0.0		0	ERAS	
2	2001-05-01 00:00:00		44.0		-9.5		4.0290069580078125		284.54663059375		0.000376245178222656		0.0		0	ERAS	
3	2001-05-01 00:00:00		44.0		-9.25		3.7846319580078125		284.366943359375		0.0004377351123046875		0.0		0	ERAS	
4	2001-05-01 00:00:00		44.0		-9.0		3.5719737080078125		284.185302734375		0.0004477500915527344		0.0		0	ERAS	
5	2001-05-01 00:00:00		44.0		-8.75		3.3952178955078125		284.093505859375		0.00046253204345703125		0.0		0	ERAS	
6	2001-05-01 00:00:00		44.0		-8.5		3.2711844380078125		284.152099609375		0.00045106793166015625		0.0		0	ERAS	
7	2001-05-01 00:00:00		44.0		-8.25		3.1966737080078125		284.378662109375		0.000409126281175628125		0.0		0	ERAS	
8	2001-05-01 00:00:00		44.0		-8.0		3.2877940205078125		284.7849117109375		0.000314357281119140625		0.0		0	ERAS	
9	2001-05-01 00:00:00		44.0		-7.75		3.2406210205078125		285.0440381094375		7.24783488466175e-05		0.0		0	ERAS	
10	2001-05-01 00:00:00		44.0		-7.5		3.0797882080078125		285.154052734375		4.291534423828125e-06		0.0		0	ERAS	
11	2001-05-01 00:00:00		44.0		-7.25		2.8999053955078125		285.216318359375		7.10467365722562e-05		0.0		0	ERAS	
12	2001-05-01 00:00:00		44.0		-7.0		2.4616343455078125		285.210693359375		0.000102996626171875		0.0		0	ERAS	
13	2001-05-01 00:00:00		44.0		-6.75		2.3551788330078125		285.097412109375		0.000102996626171875		0.0		0	ERAS	
14	2001-05-01 00:00:00		44.0		-6.5		2.5805949450078125		285.195234609375		0.000123030329940038		0.0		0	ERAS	
15	2001-05-01 00:00:00		44.0		-6.25		2.772238330078125		285.072088339375		0.00011730194891794375		0.0		0	ERAS	
16	2001-05-01 00:00:00		44.0		-6.0		3.0993194580078125		284.980224609375		8.5830688476525e-05		0.0		0	ERAS	
17	2001-05-01 00:00:00		44.0		-5.75		3.0534310205078125		284.781005859375		0.0001196681267089438		0.0		0	ERAS	
18	2001-05-01 00:00:00		44.0		-5.5		2.78259132080078125		284.628662109375		0.0001515737915035062		0.0		0	ERAS	

Figure 10. Results Parquet dataset

KPIs obtained:

- Ib02-KPI1: Time to Data Availability=2.3 s
- Ib02-KPI2: Expected Results Deviation =0

Qualitative assessment of the results

The climate scenario matches the requested targets. The scenario is seen as highly realistic, as it is gathered from historical data.

Table 8. Test case 2 for UC Ib02

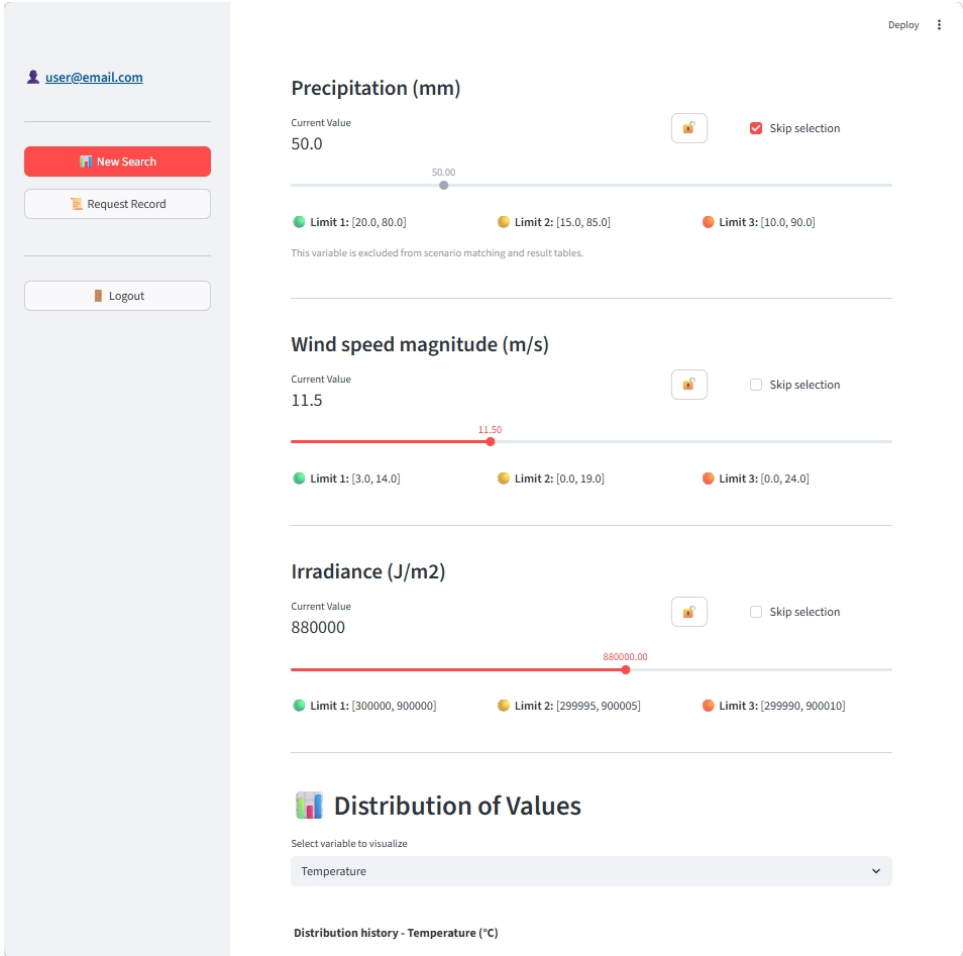
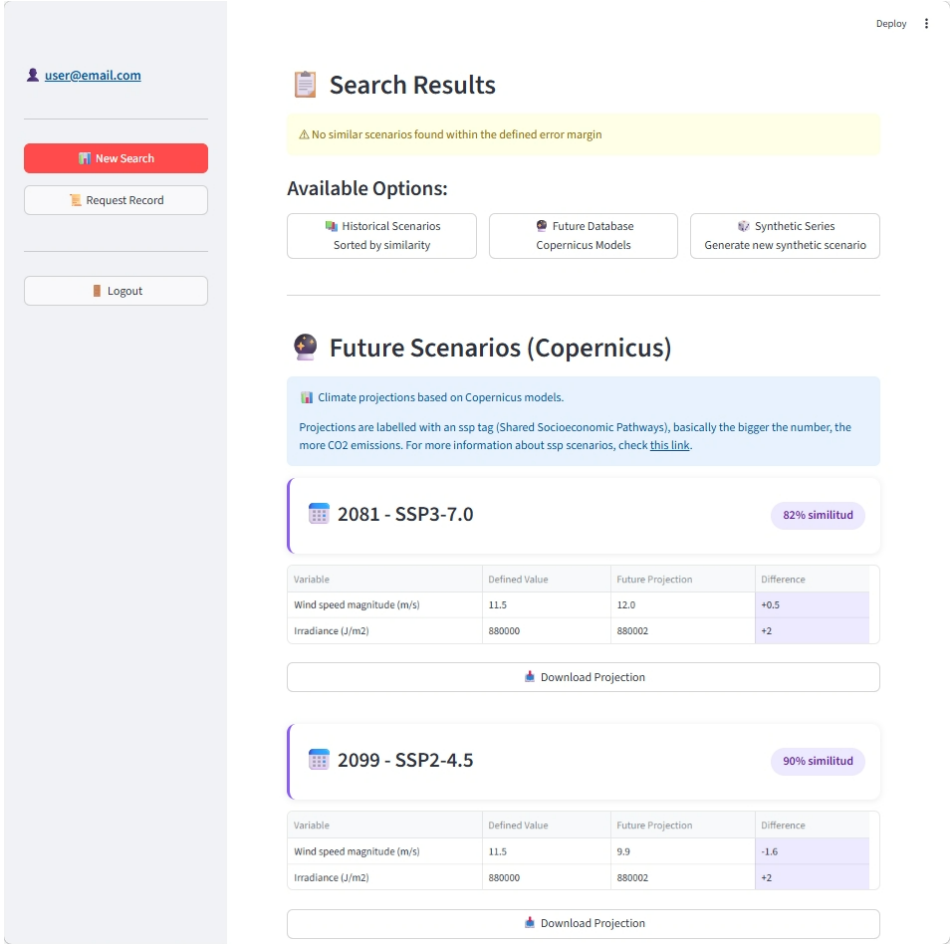
Test Case ID	TC Ib02.2
Name	Identification of a suitable future climate scenarios through Pareto optimum
Related UC	UC Ib02
Timeframe	Simulation-based experiment
Targets	Identify a synthetic climate time series with an average wind speed of 11.5 m/s and an average solar irradiance of 880,000 J/m ²
Actors involved	- REE: technical requirements definition, knowledge and data, methodology co-definition and results validation. - CIRCE: development climate scenarios catalogue and selection algorithm.
Assets and systems involved	- Future climate scenario datasets - Scenario selection algorithm
Triggering Event	User request for a synthetic climate scenario matching specified meteorological targets.  The screenshot shows a web-based interface for defining target values for a synthetic climate scenario. On the left is a sidebar with a user profile (user@email.com), a 'New Search' button, a 'Request Record' button, and a 'Logout' button. The main content area displays three sliders for different meteorological variables: Precipitation (mm), Wind speed magnitude (m/s), and Irradiance (J/m2). Each slider has a 'Current Value' field, a 'Skip selection' checkbox, and three limit ranges (Limit 1, Limit 2, Limit 3). For Precipitation, the current value is 50.0 and it is noted as excluded from scenario matching. For Wind speed magnitude, the current value is 11.5. For Irradiance, the current value is 880000. Below the sliders is a 'Distribution of Values' section with a dropdown menu set to 'Temperature' and a 'Distribution history' label.

Figure 11. Target Definition Interface - TC Ib02.2

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Pre-condition	Future climate scenarios available.
Experiment description	The user defined target values of 11.5 m/s for mean wind speed and 880,000 J/m² for mean irradiance. The future scenario catalogue was explored through pareto optimum algorithms to select a synthetic climate time series matching these targets.  Figure 12. Future scenarios results.
Post-condition	A synthetic multivariate climate time series has been selected, validated, and exported in Parquet. After clicking the “download” button the user is then redirected to downloading the parquet file.

	user@email.com New Search Request Record Logout Deploy Request Record Last 10 searches Year 2081 - SSP3-7.0 26/05/2026 09:33 Temperature: 27.7°C Precipitation: 63.4 mm Irradiance: 880000 J/m2 Wind speed magnitude: 11.5 m/s Download Year 1979 24/05/2026 09:33 Temperature: 25.6°C Precipitation: 78.6 mm Irradiance: 321634 J/m2 Wind speed magnitude: 13.4 m/s Download Year 1975 29/05/2026 09:33 Temperature: 10.4°C Precipitation: 78.2 mm Irradiance: 895584 J/m2 Wind speed magnitude: 7.6 m/s Download Figure 13. Request Record – TC Ib02.2 After downloading it, the scenario is visible for all other users, ensuring easy access to already-requested data.
Datasets required for the experiment	• Future climate scenario datasets in Parquet format • Future scenarios statistical references
Field data to be gathered	• Target values • Served values • Manhattan distance to target.
Related KPIs	Ib02-KPI1: Time to Data Availability Ib02-KPI2: Expected Results Deviation
Results of the experiment	
The provided future climate scenario matches the requested targets. The resulting dataset was exported in Parquet format for subsequent power system analyses (Figure 18). The results of synthetic renewable resources series are analysed and compared with other scenarios and validated as realistic according to the request made.	

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

#	Datetime	# Latitude	# Longitude	# scenario	# origin	# 2 metre temperatura	# Irradiance	# Wind speed	# Precipitation
0	2021-09-09 12:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	293.3	823.4	3.87	1.62777e
1	2021-09-09 13:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	293.31	825.78	4.46	1.62777e
2	2021-09-09 14:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	294.82	784.9	3.62	1.62777e
3	2021-09-09 15:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	294.34	603.91	3.45	1.62777e
4	2021-09-09 16:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	294.81	595.53	5.68	1.62777e
5	2021-09-09 17:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	293.61	324.35	5.83	1.62777e
6	2021-09-09 18:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	293.64	144.04	6.42	1.62777e
7	2021-09-09 19:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	293.56	13.79	8.17	1.62777e
8	2021-09-09 20:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	292.83	0.0	9.21	1.62777e
9	2021-09-09 21:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	291.26	0.0	8.57	1.62777e
10	2021-09-09 22:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	290.83	0.0	7.93	1.62777e
11	2021-09-09 23:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	289.95	0.0	7.01	1.62777e
12	2021-09-10 00:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	289.6	0.0	6.27	0.00011796
13	2021-09-10 01:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	289.52	0.0	5.37	0.00011796
14	2021-09-10 02:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	289.45	0.0	5.22	0.00011796
15	2021-09-10 03:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	287.53	0.0	4.92	0.00011796
16	2021-09-10 04:00:00	38.75	-4.5	wp3-7.0	CMCC-CM2-SR5	287.72	0.0	4.33	0.00011796

Figure 14. Results Parquet dataset

KPIs obtained:

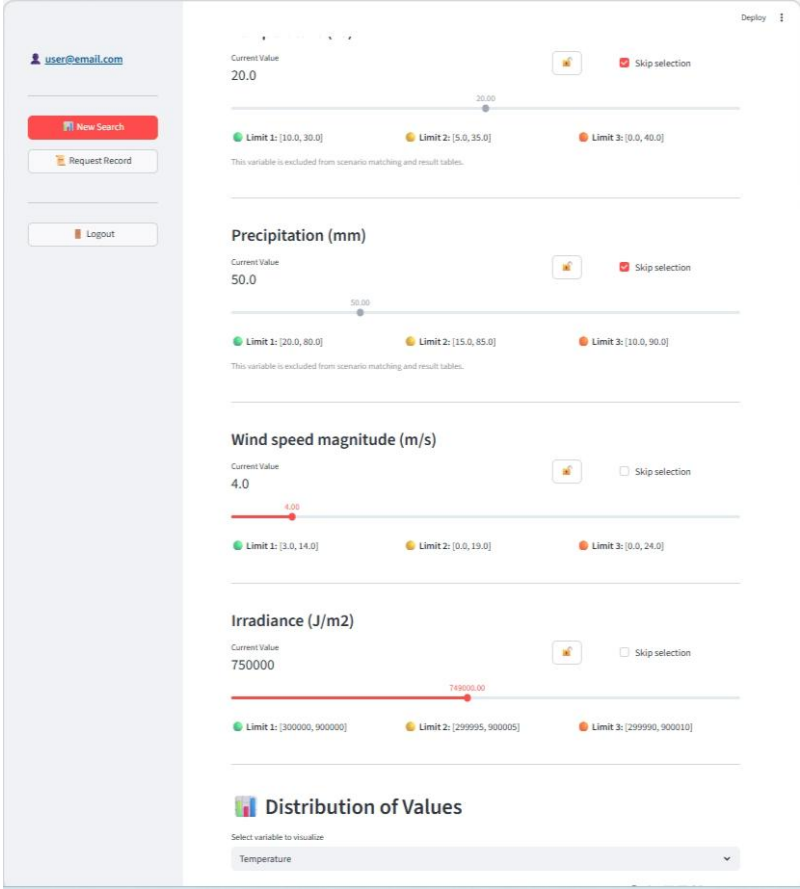
- Ib02-KPI1: Time to Data Availability=2.8 s
- Ib02-KPI2: Expected Results Deviation =0.01

Qualitative assessment of the results

The provided data comes from a climate data model, which starts at present day and then repeatedly forecasts the next timestep until it reaches 2100. For this reason, the data may not be as realistic as that from historical observations.

Table 9. Test case 1 for UC Ib03

Test Case ID	TC Ib02.3
Name	Generation of Target-Oriented Synthetic Climate Scenarios through Multi-Objective Latent Space Exploration
Related UC	UC Ib02
Timeframe	Simulation-based experiment (offline validation).
Targets	Generate a synthetic climate time series with an average wind speed of 4.0 m/s and an average solar irradiance of 750,000 J/m ²
Actors involved	• CIRCE: development synthetic series generator. • REE: technical requirements, knowledge and results validation.
Assets and systems involved	Climate scenario generation platform, ERA5 datasets, future climate scenario datasets, 3D U-Net + VAE model, PCA module, NSGA-II optimization engine, validation and visualization modules

Triggering Event	User request for the generation of a synthetic climate scenario matching specified meteorological targets.  The screenshot displays a web interface for defining target values for a synthetic climate scenario. It features a sidebar with a user profile (user@email.com), a 'New Search' button, a 'Request Record' button, and a 'Logout' button. The main area contains four sliders for different meteorological variables: Temperature (Current Value: 20.0), Precipitation (mm) (Current Value: 50.0), Wind speed magnitude (m/s) (Current Value: 4.0), and Irradiance (J/m2) (Current Value: 750000). Each slider has three limit ranges: Limit 1 (green), Limit 2 (yellow), and Limit 3 (orange). A 'Skip selection' button is present for each variable. Below the sliders is a 'Distribution of Values' section with a dropdown menu set to 'Temperature'. <i>Figure 15. Target Definition Interface - TC Ib02.3</i>
Pre-condition	Trained U-Net/VAE model available PCA components generated NSGA-II optimization configured Historical climate dataset available.
Experiment description	The user defined target values of 4.0 m/s for mean wind speed and 750,000 J/m² for mean irradiance. The latent space of the trained model was explored through PCA and NSGA-II optimization to generate a synthetic climate time series matching these targets while preserving physical consistency and spatial-temporal coherence.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

	Deploy ⓘ user@email.com New Search Request Record Logout Search Results No similar scenarios found within the defined error margin Available Options: Historical Scenarios Sorted by similarity Future Database Copernicus Models Synthetic Series Generate new synthetic scenario Request received! Our server has correctly received your request to generate a synthetic scenario based on the parameters you defined. The synthetic scenario will be generated and sent to user@email.com in the next few minutes. You will receive a notification by email when the scenario is ready. Historical Scenarios sorted by similarity The following scenarios have at least one variable outside the acceptable range, but are the closest matches found in our historical database. 1992 78% similitud Figure 16. Synthetic series request received from user
Post-condition	A synthetic multivariate climate time series has been generated, validated, and exported in Parquet format together with the associated optimization metrics and physical plausibility indicators. The generated data is sent asynchronously to the user, and the request is saved in the request record for easier access by colleagues.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

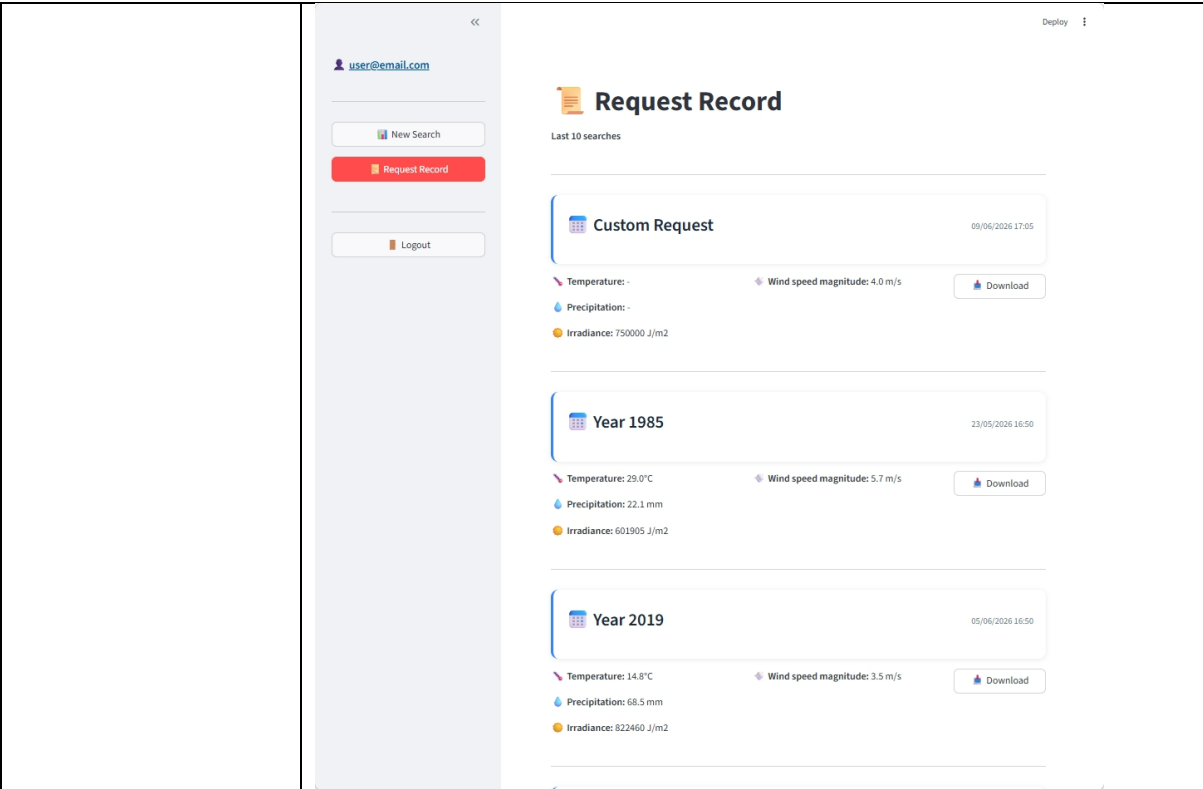


Figure 17. Request Record – TC Ib02.3

Datasets required for the experiment	• ERA5 climate datasets • Future climate scenario datasets in Parquet format • Normalization parameters (scaler.pt) • Trained PCA model • Historical statistical reference records
Field data to be gathered	• Target values • Generated values • Manhattan distance to target, distance to nearest historical scenario, physical plausibility indicators.
Related KPIs	Ib02-KPI1: Time to Data Availability Ib02-KPI2: Expected Results Deviation

Results of the experiment

The generated scenario achieved values very close to the requested targets. The optimization process produced a synthetic climate time series whose average wind speed and irradiance closely matched the specified objectives while remaining physically plausible. The resulting dataset was exported in Parquet format for subsequent energy-system analyses (Figure 18).

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

# Datetime	# Latitude	# Longitude	# scenario	Δ origin	# Wind speed	# Irradiance
3000-01-01 00:00:00	36.0	-10.0	0 inferencia	12.66053	176373.94	
3000-01-01 00:00:00	36.0	-9.75	0 inferencia	12.659311	60720.902	
3000-01-01 00:00:00	36.0	-9.5	0 inferencia	11.933801	69389.055	
3000-01-01 00:00:00	36.0	-9.25	0 inferencia	12.157175	75879.3	
3000-01-01 00:00:00	36.0	-9.0	0 inferencia	12.536136	68293.96	
3000-01-01 00:00:00	36.0	-8.75	0 inferencia	12.73115	71042.7	
3000-01-01 00:00:00	36.0	-8.5	0 inferencia	13.140312	61670.863	
3000-01-01 00:00:00	36.0	-8.25	0 inferencia	13.633192	60622.496	
3000-01-01 00:00:00	36.0	-8.0	0 inferencia	14.0211525	57981.375	
3000-01-01 00:00:00	36.0	-7.75	0 inferencia	14.646498	59909.6	
3000-01-01 00:00:00	36.0	-7.5	0 inferencia	15.27549	56778.664	
3000-01-01 00:00:00	36.0	-7.25	0 inferencia	16.06536	57198.895	
3000-01-01 00:00:00	36.0	-7.0	0 inferencia	17.054775	53895.19	
3000-01-01 00:00:00	36.0	-6.75	0 inferencia	17.911142	51703.152	
3000-01-01 00:00:00	36.0	-6.5	0 inferencia	18.724083	48624.473	
3000-01-01 00:00:00	36.0	-6.25	0 inferencia	20.373064	43983.906	
3000-01-01 00:00:00	36.0	-6.0	0 inferencia	21.87996	35589.145	

Figure 18. Results Parquet dataset

KPIs obtained:

- Ib02-KPI1: Time to Data Availability=35.93 minutes
- Ib02-KPI2: Expected Results Deviation=0.033

Qualitative assessment of the results

The histogram-based validation, Figure 19, shows that the generated scenario is located very close to the requested target in the meteorological feature space. The reported Manhattan distance between the target and the generated sample is 0.033, indicating a very high degree of agreement. Furthermore, the generated scenario remains within the distribution of historically observed climate conditions, demonstrating that the optimization process successfully balances target matching and climatological realism.

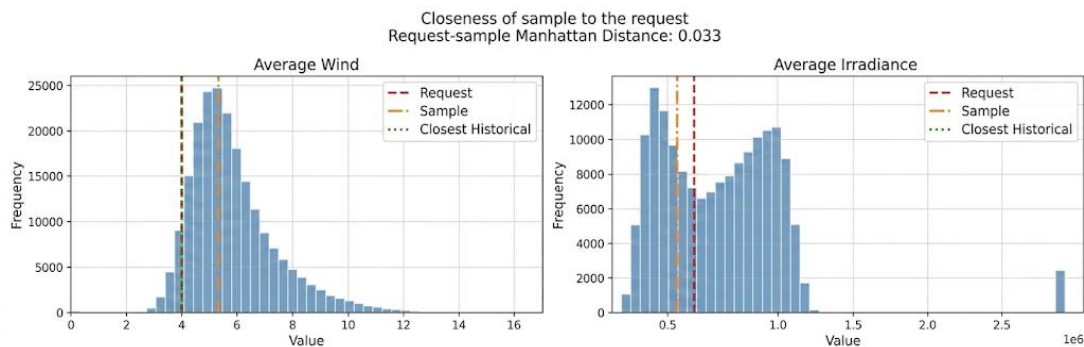


Figure 19. Histogram – Manhattan distance

Table 10. Key Performance Indicator 1 for Use Case Ib02

KPI ID	Ib02-KPI1
KPI Name	Time to Data Availability
Related Use Case	Ib02
KPI Description	Time elapsed between a user's query submission and the moment the requested data becomes available for access or download
KPI Formula	N/A
Variables explanation	N/A
Unit of measurement	Seconds (s), millisecond (s) or minutes(m)
Baseline	N/A
Reference signal(s)	N/A
Comments	N/A

Table 11. Key Performance Indicator 2 for Use Case Ib02

KPI ID	Ib02-KPI2
KPI Name	Expected Results Deviation
Related Use Case	Ib02
KPI Description	Aggregate absolute difference between the expected results and the actual results, calculated using Manhattan.
KPI Formula	$D_{L1}(E, A) = \sum_{i=1}^n e_i - a_i $
Variables explanation	e_i: expected results (normalized) a_i: actual results (normalized)
Unit of measurement	-
Baseline	N/A
Reference signal(s)	N/A
Comments	N/A

3.2 Cuerva's distribution grid

3.2.1 Overview of Cuerva's distribution Grid

Cuerva offers its Living Lab to the project, which is part of the company's distribution network. This Living Lab boasts high digitalization, enabling the collection of data from the network with high granularity (down to minute-level in some cases), as well as providing the necessary information for all digital twin modelling.

Cuerva's network includes more than 200 prosumers, collectively generating over 750 kW of renewable energy for self-consumption. The network includes energy communities, electric vehicles, and behind-the-meter batteries, showcasing our commitment to sustainable energy practices. Additionally, we host photovoltaic self-consumption systems totalling approximately 95 MW,

From the physical infrastructure side, Cuerva has a highly digitized network with the following measuring equipment:

- +5500 users (residential, commercial, and industrial)
- 2 substations
- 220/132 kV 1x160 MVA connected to REE
- 132/66/20 kV
- 31 km of HT lines
- 292 km of MT lines
- 315 km of LT lines
- 100% penetration of Smart Meters, both residential and industrial level
- High-resolution measuring devices in MV
- High-resolution measuring devices in LV

The structure illustrating the measurement map can be viewed in the following image.

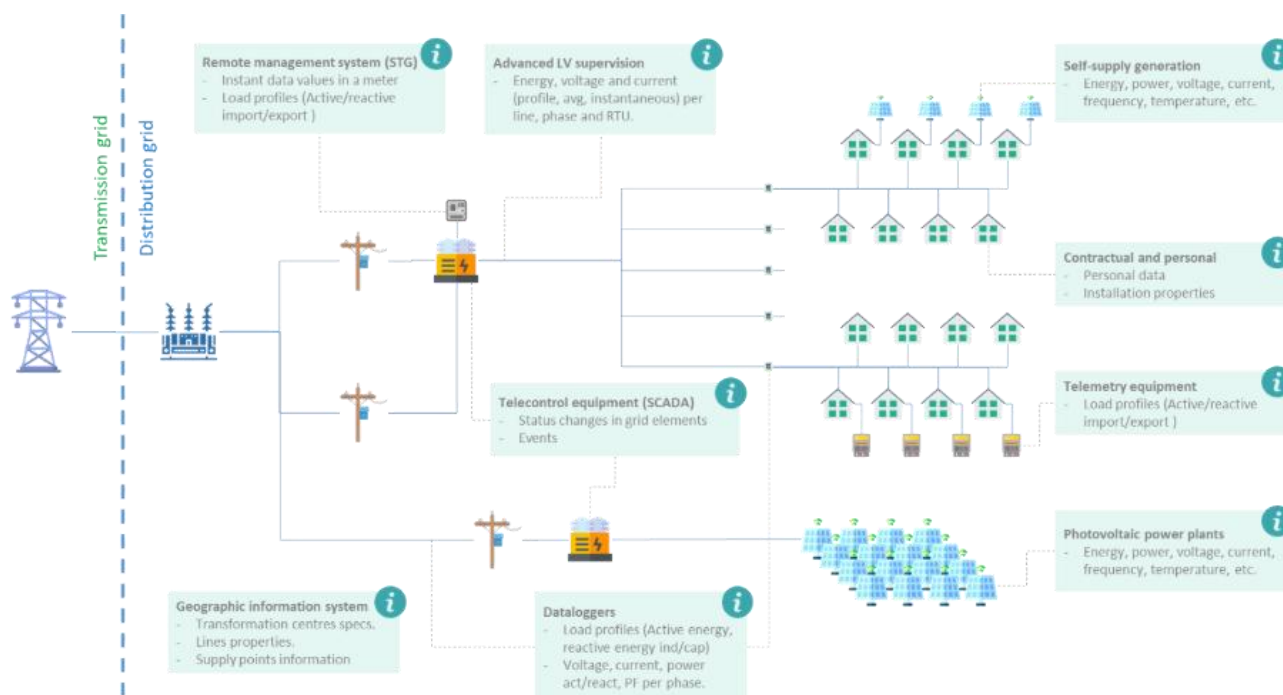


Figure 20. Measurement map for the Cuerva's living lab

3.2.2 Use Cases Related to Cuerva

Adaion and Cuerva contribute to TwinEU through the implementation of advanced distribution network digital twin functionalities focused on flexibility management, congestion mitigation, and the integration of electric mobility in medium- and low-voltage grids. The Cuerva demonstrator explores how digital twins can support Distribution System Operators (DSOs) in operating increasingly flexible and decentralized networks while minimizing the need for costly conventional grid reinforcement.

The Cuerva use cases are centred on two complementary scenarios:

- **UC Ib08 – Long-term flexibility in MV**, addressing congestion management through flexibility services.
- **UC Ib09 – Flex Connections**, focused on the integration of Electric Vehicle (EV) charging infrastructure while maintaining voltage quality and grid stability.

Both use cases leverage the Cuerva network digital twin together with data analytics, and flexibility activation mechanisms to improve operational efficiency and support the transition towards more resilient and sustainable distribution grids.

UC Ib08 – Long-term flexibility in MV

This use case investigates how long-term flexibility services can be used in medium-voltage networks to prevent congestion and defer traditional grid reinforcement investments. Instead of relying exclusively on capital-intensive solutions such as new lines or transformer upgrades, the proposed approach evaluates the use of demand response, distributed energy resource (DER) management, and predictive analytics to dynamically balance generation and consumption.

The use case addresses the increasing operational complexity associated with renewable energy integration, changing demand profiles, and the electrification of end uses. The Cuerva digital twin is used to analyse network behaviour, identify future congestion risks, and determine the flexibility requirements needed to maintain reliable operation under different planning and operational scenarios.

The implementation combines:

- Flexibility resource identification
- Demand response mechanisms
- Predictive analytics for congestion anticipation and operational optimization

The main expected outcomes include:

- Reduction of overload situations
- Improved utilization of available flexibility resources
- Reduction of CAPEX and OPEX compared to conventional reinforcement approaches
- Increased resilience and operational efficiency of the distribution grid.

The use case also evaluates the availability and reliability of flexibility services as key indicators for future scalability and replicability.

UC Ib09 – Flex Connections

The second Cuerva use case focuses on the integration of EV charging infrastructure into MV and LV distribution grids through flexible connection schemes. The rapid deployment of EV chargers can significantly impact voltage quality and grid stability, traditionally requiring reinforcement measures or closed-ring operation strategies. This use case investigates an alternative approach based on operational flexibility and controllable charging strategies.

The core objective is to determine flexibility requirements for EV chargers during both planning and operational stages in order to maintain acceptable voltage profiles while avoiding unnecessary infrastructure upgrades. The Cuerva digital twin enables the simulation and assessment of different charging scenarios, helping the DSO evaluate the impact of EV penetration levels and optimise grid operation accordingly.

The proposed flexibility approach includes:

- Dynamic management of EV charging demand
- Adaptation of charging patterns according to grid conditions
- Coordination between EV flexibility services and grid operation constraints
- Integration of advanced monitoring and control mechanisms

Through these mechanisms, EV charging can become an active flexibility resource capable of supporting voltage regulation and load balancing in the distribution network.

The main expected benefits include:

- Improved voltage quality across MV and LV feeders
- Enhanced grid stability under high EV penetration scenarios
- Increased load balancing efficiency
- More efficient utilization of existing network infrastructure

This use case demonstrates how flexible EV integration can support the large-scale electrification of transport while reducing the need for conventional grid reinforcement investments.

3.2.3 Methodology for Implementation

The optimisation of distribution grid capacity remains a foundational bottleneck for the integration of new renewable generation and electrification loads. Traditionally, Grid Operators granted network access under Firm Connection Agreements, which guarantee the total contracted capacity constantly throughout the entire year based on worst-case peak-load scenarios. While reliable, this conservative approach results in severe grid under-utilisation and long queues for new interconnection applicants. The same conservative assumptions also constrain the DSO's ability to actively coordinate DERs and flexibility resources, since static peak-based limits do not reveal the temporal margins where flexibility can be safely activated.

To overcome these structural inefficiencies, this Digital Twin implementation introduces a single data-driven methodological pipeline that powers both Cuerva demonstrations. The pipeline operates a temporal modulation of grid capacity based on observed network behaviour: rather than treating

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

the year as a single worst-case window, it identifies a small number of statistically distinct operating states (clusters) that describe how the network actually behaves over time.

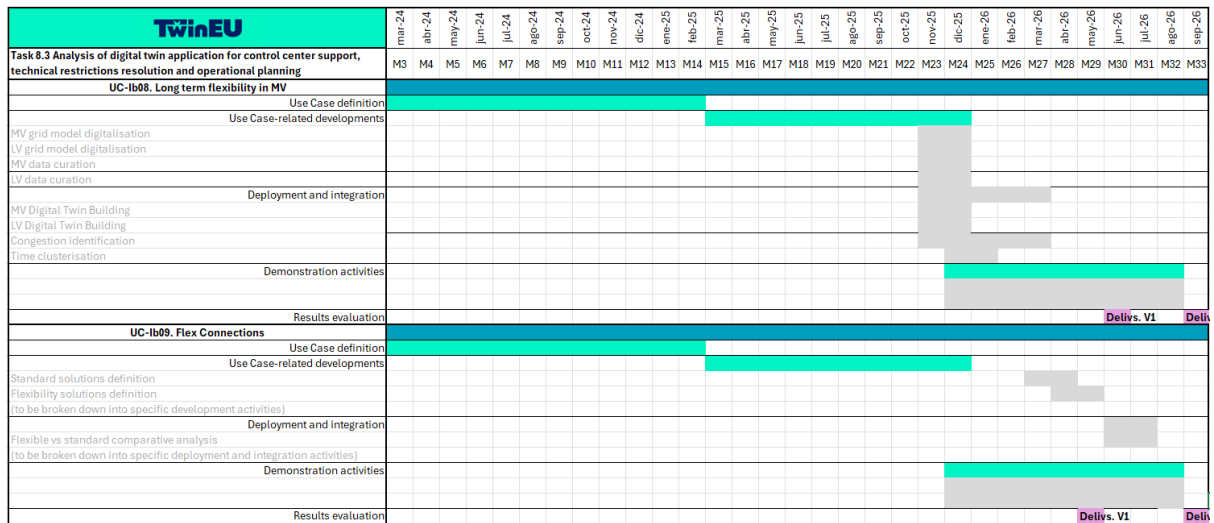


Figure 21. Cuerva's grid use cases development plan

Once these clusters are available, two downstream applications consume them:

- **Demo 1 — Long Term Flexibility in MV:** the clusters are used to drive the activation logic for DERs and flexible assets. Each cluster characterises a recurring grid state, and the Digital Twin issues dispatch signals (consumption up/down, generation up/down) aligned with the cluster's temporal pattern, in order to relieve congestion and increase the effective utilisation of the network.
- **Demo 2 — Flexible Connections:** the clusters are translated into a time-of-use capacity offer that the DSO can return to a connection applicant. Instead of a single firm power figure, the applicant receives a contractual schedule of capacity tiers aligned with the cluster blocks.

The methodological architecture deployed within this Digital Twin framework therefore operates as a three-stage algorithmic pipeline focused on balancing network safety with operational and contractual flexibility:

- **Data Quality Assurance, Pre-Processing and Filtering:** Filtering and preparing raw substation data to ensure statistical relevance.
- **Unsupervised Machine Learning Segmentation:** Grouping the 8,760 hours of the year into distinct, statistically homogeneous capacity clusters.
- **Operational Smoothing and Time-Block Optimisation:** Refining raw mathematical clusters into operational, contractually usable time blocks.

Step 1: Data Pre-Processing and Quality Control

The pipeline processes raw consumption data measured at the secondary side of distribution transformers. This data is aggregated by phase to establish a robust baseline of net load. To prevent non-representative or corrupt datasets from biasing the machine learning segmentation, the Digital Twin applies a rigid Multi-Criteria Statistical Filter.

This pre-processing framework evaluates the dataset across several key dimensions without altering the underlying grid profile:

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

- **Activity Verification:** Discards monitoring nodes that exhibit prolonged inactivity or zero-load profiles that do not represent active network behaviour.
- **Volatility and Outlier Mitigation:** Identifies and flags extreme, non-ergodic anomalies or measurement noise that could distort the machine learning clustering engine.
- **Operational Relevance Filtering:** Ensures that the processed substations exhibit typical peak and valley behaviours necessary to model grid flexibility safely.

By filtering data through these high-level statistical bounds, the framework guarantees that the subsequent segmentation models reflect systemic grid realities rather than measurement artefacts.

Step 2: Unsupervised Clustering Engine

The core engine segments the time domain by treating the 8,760 hours of the annual cycle as individual multi-dimensional observations. Instead of enforcing arbitrary, pre-defined regulatory schedules, the Digital Twin utilises an unsupervised clustering approach to uncover natural consumption states and latent network behaviours.

To characterise each temporal window effectively, the engine uses a multi-dimensional feature space:

- **Aggregate Load Profiles:** Tracks the typical load magnitudes and statistical boundaries across the monitored assets.
- **Temporal and Chronological Context:** Accounts for cyclical variations across daily, weekly, and seasonal periods.
- **Cyclic Continuity Parameters:** Applies continuous mathematical formulations to ensure smooth transitions between chronological boundaries (e.g., day-to-night and seasonal adjustments), avoiding artificial data breaks at midnight or month-ends.

The optimisation space restricts the final cluster cardinality to a bounded range (typically between 3 and 7 clusters). Limiting the number of segments prevents over-fragmentation of the time domain, ensuring that the resulting profiles remain clear enough for network operators to dispatch DERs against (Demo 1) and for connection applicants to realistically contract against (Demo 2).

Step 3: Operational Smoothing and Time-Block Optimisation

While standard unsupervised clustering yields statistically robust groups, raw machine learning outputs tend to exhibit high temporal fragmentation, such as short-lived oscillations or isolated single-hour cluster assignments. Frequent modifications to capacity limits or DER dispatch signals are commercially and operationally unviable for network utilities, so a programmatic post-processing engine is introduced.

This deterministic layer refines raw mathematical clusters into stable, continuous time blocks, governed by a sequence of strict operational boundaries:

- **Peak Capacity Preservation:** Ensures that time-block aggregation never artificially masks or miscalculates critical peak network loads.
- **Boundary Stability:** Smooths out high-frequency oscillations and eliminates isolated temporal “islands” below a target hourly duration threshold, merging them logically into adjacent dominant clusters.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

- **Geometric Profile Regularisation:** Normalises irregular or disjointed time profiles into continuous rectangular blocks, establishing predictable and dependable daily or weekly capacity schedules.
- **Cardinality Consistency:** Maintains the pre-defined number of operational segments throughout the smoothing cycle, ensuring no valid grid state is prematurely eliminated.

The resulting output is a highly structured time-of-use capacity map. This map is the common artefact that both demonstrations consume: it bounds the DER dispatch logic of Demo 1 within predictable activation windows, and it defines the contractually viable time tiers of the capacity offers issued in Demo 2.

Key Performance Indicators (KPIs) for Segmentation Optimisation

To objectively quantify, track, and optimise the performance of the temporal segmentation engine within the TwinEU Digital Twin framework, five core KPIs are established alongside an independent Result Validation Indicator (RVI). Because the segmentation engine is the shared backbone of both Cuerva demonstrations, these KPIs apply uniformly to both use cases.

- **Intra-Period Volatility (KPI1):** Evaluates the stability and predictability of electrical consumption within each designated cluster period. Lower volatility ensures that historical data averages reflect dependable operating conditions, allowing the Digital Twin to safely issue DER dispatch signals (Demo 1) and to safely calculate flexible capacity limits (Demo 2) without endangering grid stability.
- **Inter-Network Heterogeneity (KPI2):** Measures the synchronisation of load behaviour across the entire fleet of transformers within a given cluster period. High homogeneity ensures that the resulting temporal segments represent systemic, macro-level grid behaviours rather than being skewed by localised anomalies.
- **Temporal Fragmentation (KPI3):** Tracks the number of short, highly volatile cluster allocations throughout the annual calendar. Minimising this index is the primary objective of the post-processing smoothing stage, shifting the model from a purely mathematical grouping to a contractually and operationally viable scheduling system.
- **Operational Complexity (KPI4):** Assesses the administrative and operational feasibility of the generated cluster model relative to distribution network constraints, penalising configurations that exceed regulatory or practical limits for time-block management.
- **Multi-Objective Global Segmentation Score (KPI5):** Compiles KPI1 to KPI4 into a single comprehensive objective index. It acts as the optimisation fitness function for the segmentation engine, balancing statistical accuracy against operational constraint compliance.
- **Result Validation Indicator (RVI):** Quantifies the capacity spread between the highest-load cluster (system peak) and the lowest-load cluster (system valley). A high differentiation range proves that the algorithm has identified distinct, high-contrast network utilisation states; this is the ultimate yardstick of how much underutilised hosting capacity can be released, either by activating flexibility (Demo 1) or by granting time-dependent connection capacity (Demo 2).

3.2.3.1 Demo 1 — Long Term Flexibility in MV

Demo 1 addresses the active management of grid capacity through the coordinated dispatch of Distributed Energy Resources and other flexible assets connected to Cuerva's MV grid. The objective is to release additional hosting capacity for renewable generation, and electrification loads without reinforcing the physical infrastructure, by leveraging the controllability of DERs to mitigate congestion when and where it occurs.

Once the segmentation pipeline described above has produced the annual time-of-use capacity map, each cluster represents a recurring grid state characterised by a typical load level, a typical volatility, and a defined temporal footprint. Demo 1 consumes this map as the activation grammar for flexibility:

- **State-aware signalling:** Each cluster identifies a recurring grid state. Because the post-processed clusters are stable, contiguous time blocks, they can be used directly as activation windows for DER dispatch signals, avoiding the operational risk of high-frequency switching.
- **Direction of flexibility:** For peak-load clusters, the Digital Twin issues signals requesting flexible consumers to reduce consumption and/or flexible generators to increase production, in order to relieve congestion. For valley clusters, it issues signals to increase consumption and/or reduce curtailment, allowing the network to absorb additional energy and improving the utilisation of available capacity.
- **Magnitude of the request:** The capacity headroom available for activation within each cluster is bounded by the cluster's statistical profile and by the safety margins enforced by the Multi-Criteria Statistical Filter and the Peak Capacity Preservation constraint. KPI1 (Intra-Period Volatility) sets the upper bound on how aggressively flexibility can be requested inside each block without endangering grid stability.
- **Long-term coordination:** Because the cluster schedule is stable across the annual cycle, it supports the long-term coordination of DERs and the design of recurring flexibility products, rather than purely reactive activations.

The result is a flexibility activation framework that is fully grounded in the observed behaviour of the network. The success of Demo 1 is measured indirectly through the same five KPIs and the RVI: a high RVI combined with a low KPI1 indicates that there is a wide, dependable capacity gap between peak and valley clusters that flexibility activations can exploit.

3.2.3.2 Demo 2 — Flexible Connections

Demo 2 addresses the access and connection process from the perspective of new applicants requesting capacity from the Cuerva grid — with the deployment of electric vehicle (EV) charging infrastructure taken as the reference example. Under the conventional firm connection regime, such an applicant receives a binary answer (granted or denied) at a single firm power level dimensioned for the worst-case peak. This conservative answer routinely denies access to capacity that the network in fact possesses during a large fraction of the year.

Flexible Connections replace the binary answer with a time-dependent capacity offer built directly on the cluster map produced by the segmentation pipeline:

- **Capacity tiers per cluster:** Each cluster in the post-processed map defines a contractable capacity tier. Low-load clusters expose the largest available headroom and translate into the

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

highest power limits offered to the applicant; high-load clusters expose the smallest headroom and translate into reduced limits, protecting the grid during peak conditions.

- Operationally usable schedule: Because clusters are smoothed into continuous rectangular time blocks (KPI3, KPI4), the offer takes the form of a structured weekly/seasonal schedule that the applicant can plan and operate against. For an EV charging operator, this directly determines when fast-charging power levels are available and when reduced power applies.
- Safety-bounded headroom: The maximum capacity offered in each tier is bounded by the cluster's statistical envelope and by the Peak Capacity Preservation constraint, ensuring that flexible access does not erode the firm capacity required to maintain grid integrity.
- Released hosting capacity: The aggregate effect of the offer is quantified by the Result Validation Indicator (RVI): the wider the contrast between peak and valley clusters, the more capacity the DSO can responsibly grant to the applicant in addition to the conservative firm baseline.

As a result, applicants such as EV charging operators receive a usable, predictable connection schedule that aligns their operation with the network's temporal capacity profile. The same five KPIs and the RVI defined for the segmentation pipeline serve as the performance metrics for this demonstration, since the contractual quality of the offer is a direct consequence of the statistical and operational quality of the underlying clusters.

3.2.4 Testing Scenarios and Performance Metrics

Because both Cuerva demonstrations share the same methodological backbone — the temporal segmentation pipeline described in Section 3.2.3 — the testing scenario and the associated KPIs are defined once and apply jointly to UC Long Term Flexibility in MV and UC Flex Connections. The test case validates the engine that produces the time-of-use capacity map; the demo-specific value (DER dispatch logic, capacity offers) is then derived deterministically from that map as described in 3.2.3.1 and 3.2.3.2.

Test Case — Temporal Segmentation of Grid Capacity

The table below presents the test case that demonstrates the segmentation pipeline on historical substation consumption data from Cuerva's MV grid.

Table 12. Test case 1 in Cuerva's grid

Test Case ID	TC Ib_CUERVA.1
Name	Temporal Segmentation of Grid Capacity — Common Engine for Long Term Flexibility and Flexible Connections
Related UC	UC Long Term Flexibility in MV (CUERVA & ADAION) UC Flex Connections (CUERVA & ADAION)
Timeframe	July 2025 – August 2026
Targets	Validate the Digital Twin segmentation pipeline that constitutes the common methodological foundation for the two Cuerva use cases (Long Term Flexibility and Flexible Connections). Demonstrate that the unsupervised clustering and post-processing stages produce a stable, operationally viable time-of-use capacity map that can be subsequently consumed by (i) the DER dispatch logic in the Long-Term Flexibility demo and (ii) the time-dependent capacity-offer logic in the Flexible Connections demo.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Actors involved	CUERVA — DSO. Provides historical and real-time substation consumption data and validates the operational viability of the resulting time blocks. ADAION — Digital Twin technology provider. Deploys and operates the segmentation pipeline.
Assets and systems involved	Cuerva SCADA and AMR metering data (active power at the secondary side of MV/LV distribution transformers). Monitoring nodes across the Cuerva MV network.
Triggering Event	On-demand execution of the segmentation pipeline on a defined annual dataset. The resulting clusters subsequently feed both demonstration use cases.
Pre-condition	At least 8,760 hourly measurement records available per monitored transformer. Data quality pre-screening completed (activity verification, outlier flagging). Digital Twin platform and segmentation engine deployed and integrated.
Experiment description	Using historical hourly consumption records at the secondary side of distribution transformers: 1. Apply the Multi-Criteria Statistical Filter to verify data quality: activity verification, volatility and outlier mitigation, and operational relevance filtering. 2. Run the unsupervised clustering engine on the validated 8,760-hour annual dataset, using a multi-dimensional feature space (aggregate load profiles, temporal context, cyclic continuity parameters), constraining cluster cardinality to 3–7 groups. 3. Apply the operational smoothing and time-block optimisation post-processing stage to eliminate high-frequency oscillations and isolated single-hour cluster assignments, producing stable continuous rectangular time blocks. 4. Evaluate the resulting segmentation against the five KPIs: Intra-Period Volatility (KPI1), Inter-Network Heterogeneity (KPI2), Temporal Fragmentation (KPI3), Operational Complexity (KPI4), and the Multi-Objective Global Segmentation Score (KPI5). 5. Compute the Result Validation Indicator (RVI) as the capacity spread between the peak and valley clusters to quantify the effective gain in accessible hosting capacity. 6. Publish the resulting time-of-use capacity map to both downstream applications: the DER signalling logic (Long Term Flexibility) and the connection-offer engine (Flexible Connections).
Post-condition	A validated set of operational time blocks (between 3 and 7 capacity tiers) covering the full annual cycle is produced. KPI1 to KPI5 and the RVI are computed and stored. The capacity map is made available to both Cuerva demonstration use cases.
Datasets required for the experiment	Historical hourly active power measurements at secondary transformer level (minimum 12 months). Transformer network metadata (location, rated capacity).
Field data to be gathered	Number of valid monitoring nodes after pre-processing filter. Final cluster cardinality (number of time blocks). KPI1 to KPI5 values for

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

	the optimised segmentation. RVI value (peak-to-valley capacity spread in MW and as a percentage of rated capacity). Time-block schedule (start/end hours per tier, per day type).
Related KPIs	CUERVA-KPI1: Intra-Period Volatility CUERVA-KPI2: Inter-Network Heterogeneity CUERVA-KPI3: Temporal Fragmentation Index CUERVA-KPI4: Operational Complexity CUERVA-KPI5: Multi-Objective Global Segmentation Score CUERVA-RVI: Result Validation Indicator

Results of the experiment

The segmentation pipeline was executed on the historical hourly active-power measurements collected at the secondary side of the monitored distribution transformers of Cuerva's MV Living Lab, covering a complete 12-month annual cycle (8 760 hourly records per node). After the Multi-Criteria Statistical Filter, 60 monitoring nodes were retained as statistically valid inputs to the unsupervised clustering engine. The post-processed segmentation converged to 5 operational clusters within the target cardinality range [3, 7], producing a continuous time-of-use capacity map with no sub-threshold blocks.

Qualitative assessment of the results

Compared with the conservative Firm Connection baseline dimensioned for the annual peak load, the segmentation-based capacity map exposes a substantial fraction of hosting capacity that would otherwise remain inaccessible under a single, worst-case power limit. The combination of a low KPI1, a KPI3 of zero and a fully compliant KPI4 confirms that this released headroom is not statistical noise but a stable, contractually usable set of time blocks. The methodology is therefore validated as fit for its two intended downstream applications on Cuerva's MV grid: the emission of state-aware dispatch signals to DERs and flexible assets within predictable activation windows (Demo 1), and the issuance of time-dependent capacity offers to new connection applicants such as EV charging operators (Demo 2). A single Digital Twin backbone consequently supports both flexibility activation and flexible-connection granting on the same network.

Key Performance Indicators

The following tables define the KPIs associated with the test case. The same KPI set characterises the performance of the segmentation engine for both Cuerva demonstrations.

Table 13. Key Performance Indicator 1 for Cuerva's use case

KPI ID	CUERVA-KPI1
KPI Name	Intra-Period Volatility
Related Use Case	UC Long Term Flexibility in MV & UC Flex Connections (CUERVA & ADAION)
KPI Description	Evaluates the stability and predictability of electrical consumption within each designated cluster period. Lower volatility ensures that historical data averages reflect dependable operating conditions, supporting both safe DER dispatch signalling (Demo 1) and safe time-dependent capacity offers (Demo 2).
KPI Formula	Mean of the standard deviation of load values within each cluster, normalised by the cluster mean load. Lower values indicate more stable and predictable capacity blocks.
Variables explanation	σ_k : standard deviation of load measurements within cluster k. μ_k : mean load within cluster k. K: total number of clusters.
Unit of measurement	Normalised dimensionless index (lower is better)
Baseline	To be defined using the pre-implementation firm connection baseline.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

KPI value	Target threshold: $\text{Var}(\mu)\% < 25\%$ across all operational clusters
Comments	N/A

Table 14. Key Performance Indicator 2 for Cuerva's use case

KPI ID	CUERVA-KPI2
KPI Name	Inter-Network Heterogeneity
Related Use Case	UC Long Term Flexibility in MV & UC Flex Connections (CUERVA & ADAION)
KPI Description	Measures the degree of synchronisation of load behaviour across the entire fleet of monitored transformers within a given cluster period. High homogeneity confirms that temporal segments represent systemic, macro-level grid behaviours rather than being dominated by isolated local anomalies.
KPI Formula	Ratio of between-cluster variance to total variance across all transformer nodes and time steps within the cluster assignment. Higher values indicate greater differentiation between clusters at the fleet level.
Variables explanation	V_between: variance of cluster-mean loads across all monitored transformers. V_total: total variance of all load observations.
Unit of measurement	Dimensionless ratio (higher inter-cluster differentiation is better)
Baseline	To be defined using the pre-implementation baseline.
KPI value	Target Threshold: Homog% < 15%
Comments	A high KPI2 value in combination with a low KPI1 confirms the quality of the segmentation for both DER dispatch and flexible connection offers.

Table 15. Key Performance Indicator 3 for Cuerva's use case

KPI ID	CUERVA-KPI3
KPI Name	Temporal Fragmentation Index
Related Use Case	UC Long Term Flexibility in MV & UC Flex Connections (CUERVA & ADAION)
KPI Description	Tracks the physical number of short, highly volatile cluster allocations throughout the annual calendar. High fragmentation implies constant switching of capacity limits or DER signals, introducing operational risk and breaking commercial usability.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

KPI Formula	Count of cluster-assignment transitions in the smoothed annual time series that fall below the minimum viable block duration threshold.
Variables explanation	T_min: minimum operational block duration (hours). N_short: number of time blocks shorter than T_min after post-processing smoothing.
Unit of measurement	Number of sub-threshold transitions (lower is better; target = 0)
Baseline	0 transitions (fully smooth schedule post-processing).
KPI value	Target Threshold: $Frag_{blocks} < 150$ raw blocks per year pre-smoothing; optimized down to < 10 blocks post-smoothing.
Comments	This is the primary metric targeted by the operational smoothing stage. A result of 0 confirms full operational viability for DER signalling and full contractability for connection offers.

Table 16. Key Performance Indicator 4 for Cuerva's use case

KPI ID	CUERVA-KPI4
KPI Name	Operational Complexity
Related Use Case	UC Long Term Flexibility in MV & UC Flex Connections (CUERVA & ADAION)
KPI Description	Assesses the administrative and operational feasibility of the generated cluster model relative to distribution network constraints. This metric penalises configurations that exceed regulatory or practical limits for the number of distinct time-block tiers.
KPI Formula	Binary or graded score based on whether the final cluster cardinality falls within the accepted operational range [3, 7] and whether each cluster covers a minimum annual exposure (hours per year).
Variables explanation	K_final: final number of operational clusters. K_min = 3, K_max = 7: regulatory and operational bounds for cluster cardinality.
Unit of measurement	Graded compliance score (0–1, where 1 = fully compliant)
Baseline	Full compliance with the defined cardinality range [3, 7].
KPI value	Target Threshold: $Comp_{ops} = 0$ (implying $K \leq 7$).
Comments	Configurations outside the cardinality range or with clusters covering fewer than the minimum annual hours are penalised in KPI5.

Table 17. Key Performance Indicator 5 for Cuerva's use case

KPI ID	CUERVA-KPI5
KPI Name	Multi-Objective Global Segmentation Score
Related Use Case	UC Long Term Flexibility in MV & UC Flex Connections (CUERVA & ADAION)
KPI Description	Compiles the individual optimisation metrics (KPI1 to KPI4) into a single comprehensive objective index. This master score acts as the optimisation fitness function of the segmentation engine, applying strict relative weights to balance statistical accuracy against operational constraint compliance.
KPI Formula	$KPI5 = w_1 \cdot (1 - KPI1_norm) + w_2 \cdot KPI2_norm + w_3 \cdot (1 - KPI3_norm) + w_4 \cdot KPI4_norm$, where weights w_1 – w_4 are calibrated by ADAION during pipeline configuration.
Variables explanation	KPI1_norm to KPI4_norm: min–max normalised values of each individual KPI. w_1 – w_4 : relative importance weights (sum = 1), defined during system calibration.
Unit of measurement	Dimensionless score [0–1] (higher is better)
Baseline	To be established based on reference segmentation runs during system integration.
KPI value	Target Threshold: A perfect, constraint-compliant segmentation achieves a score of 0. Increasingly negative numbers signal escalating violations of technical or operational boundaries.
Comments	This score drives the automated parameter search in the clustering engine to select the optimal number of clusters and smoothing parameters for both demonstrations.

Result Validation Indicator (RVI)

Beyond the core KPI optimisation loop, the Result Validation Indicator independently quantifies the systemic impact of the Digital Twin's segmentation on hosting capacity expansion. The RVI is the same for both demonstrations: it measures the contrast between peak and valley clusters, which is the lever exploited by DER signalling in Demo 1 and by time-dependent capacity offers in Demo 2.

Table 18. Key Performance Indicator 6 for Cuerva's use case

KPI ID	CUERVA-RVI
KPI Name	Result Validation Indicator (RVI)
Related Use Case	UC Long Term Flexibility in MV & UC Flex Connections (CUERVA & ADAION)
KPI Description	Quantifies the capacity spread and statistical distance between the highest-load cluster (system peak) and the lowest-load cluster (system valley) produced by the post-processed segmentation model. A high differentiation range demonstrates that the unsupervised learning engine has successfully identified distinct, high-contrast network utilisation states, which is the primary mechanism enabling both flexibility activation (Demo 1) and time-dependent capacity offers (Demo 2).
KPI Formula	$RVI = C_{peak} - C_{valley}$ [expressed as absolute capacity (MW) and as a percentage of rated transformer capacity]
Variables explanation	C_{peak} : mean capacity level of the highest-load cluster after post-processing smoothing. C_{valley} : mean capacity level of the lowest-load cluster after post-processing smoothing.
Unit of measurement	MW and % of rated capacity
Baseline	To be defined based on reference firm connection capacity values.
KPI value	To be determined upon experiment execution.
Comments	Maximising RVI while keeping KPI1 (Intra-Period Volatility) below threshold limits directly determines how much underutilised hosting capacity can be released, either through flexibility activations (Demo 1) or through flexible connection grants (Demo 2).

3.3 ANELL's distribution grid

3.3.1 Overview of ANELL's distribution Grid

ANELL is a Distribution System Operator (DSO) located in Catalunya, supplying 31 towns from Granollers to Camprodon. The piloted area in TwinEU takes place in area of Santa Eulàlia de Ronçana. Santa Eulàlia de Ronçana is an urban and rural area of 14 km² with a large variety of consumer profiles, from domestic, to industrial and rural. This part of the grid was chosen for (1) the high amount of photovoltaic solar panels installations, around 120, with a maximum power capacity of about 1 MW that keeps growing, as well as for (2) the advanced monitoring and control capabilities of the network that enhance the impact of the Digital Twin. This area also hosts an energy community, with around 30 residential participants, the majority with collective self-consumption schemes (PV-based).

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

In the Santa Eulàlia area, there are approximately 2,500 smart meters. The AMI allows for remote data collection regarding customers' energy consumption. It includes smart meters at the end user and DCU as well as the communication infrastructure and the information management system, BREO. The communication infrastructure consists mostly of PLC (Power Line Communication) between smart meters and DCUs and BPLC between substations or Optical Fibre and wireless LTE communications. All communications follow the PRIME [11]. Measurements are made every 15 minutes from industrial clients with higher contracted power and on an hourly basis from the remaining consumers, then collected at the DCUs and sent once a day.

The SCADA system comprises both hardware and software components. The hardware components include transformer Taps, IED (Intelligent Electronic Devices), RTU (Remote Terminal Unit) and FPI (Fault Passage Indicator), gather and feed data into the Field Controller Systems, which is then forwarded and processed, until it reaches the Control Centre Room. RTUs are used both in primary and secondary substations for monitoring and controlling field devices and assets, such as switchgears, transformers Taps, auto-reclosers, amongst others. As they are an essential part of SCADA system, they are connected to its database. Most commonly used RTUs in the system are T-300 from Schneider Electric, PRX from Sitel and iRTU from iGRID. The software used is TedisNet, operating on Windows with SQLServer databases. ANELL's distribution network DT in TwinEU is connected via the SCADA to retrieve information from all HW and SW components.

3.3.2 Use Cases Related to ANELL's grid

The use cases related to Anell are:

- **UC-Ib05:** DT-based N-1 contingency analysis
- **UC-Ib06:** DT-enabled new RES integration validated plan in the MV grid
- **UC-Ib07:** DT-based grid maintenance planning activities

The use cases proposed under the umbrella of T8.3 for their implementation in ANELL's grid DT are related in pairs.

In essence, UCs Ib05 and Ib07 are focused on analysing the operation of the grid and planning further actions related to grid resilience enhancement so that the O&M activities are more accurate. Ib05 makes use of the DT technology to obtain a set of scenarios where the grid is not N-1 contingent. If there is no result, simulated grid configuration is N-1 contingent. Ib07 adds on top an additional layer of complexity for which, the same exercise is repeated simulating a specific maintenance works expected by the DSO. This means that a line or substation will be discontinued for a specific period of time and the DT has to analyse if the grid will still be N-k contingent and the result must be iterated according to RT modification in the forecast algorithms. This will allow the DSO to reschedule or reconsider a given maintenance work because of safety or because it implies a large risk for grid disruption based on unforeseen boundary conditions.

Meanwhile, UCs Ib06 and Ib14 are focused on maximising DRES (e.g., PV) and large consumers (e.g., Data Centres) deployment in the grid without disrupting the operation of the assets or creating new congestions in the lines. UC Ib06 makes use of the DT technology to undertake dynamic simulation-based assessments on the grid's hosting capacity, identifying data-based limitations for the grid nodes. Ib17 offers exceptional added value for DRES plants developers and large consumers by leveraging the DTs federation framework proposed by TwinEU. More specifically, Ib14 proposes the establishment of an inter-DTs connection between the DSO DT and the LFMO (Local Flexibility Market

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Operator) DT to assess if a Local Flexibility Market opening can increase the power connected to the grid at specific times.

3.3.3 Methodology for Implementation

The following Gantt chart (Figure 22) depicts the overall development and demonstration plan for the Use Cases and their enabling functionalities that will allow the DT of ANELL's distribution grid to canalise the demonstration activities.

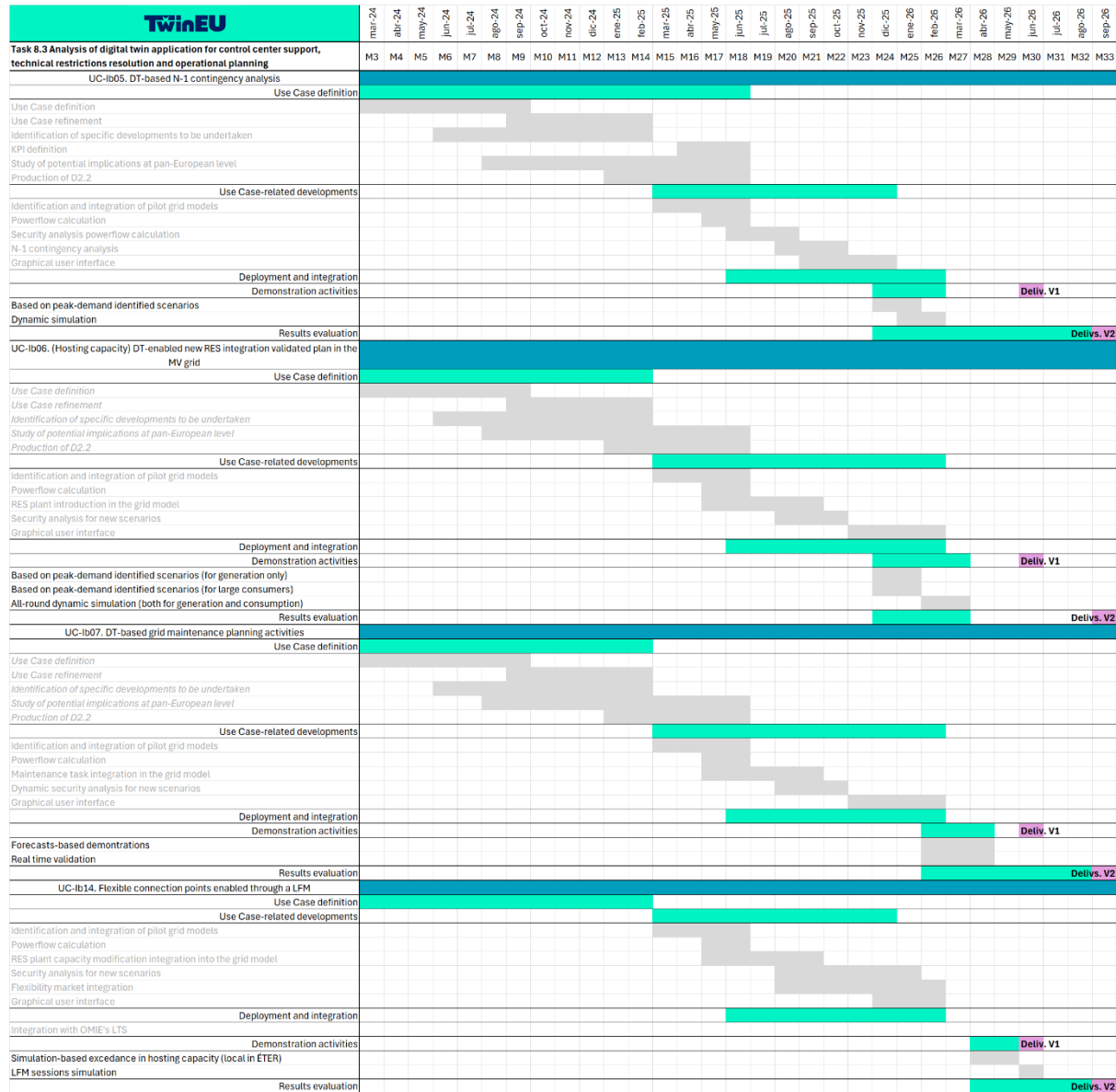


Figure 22. ANELL's Distribution Network Digital Twin development plan

3.3.4 Testing Scenarios and Performance Metrics

3.3.4.1 UC Ib05 DT-based N-1 contingency analysis

The table below presents the execution of the first experiment (test case) that demonstrates UC Ib05, where the N-1 contingency analysis has been run dynamically by the DT in short, medium and long-term forecasting horizons.

Table 19. Test case 1 for UC Ib05

Test Case ID	TC Ib05.1
Name	DT-based N-1 contingency analysis
Related UC	UC Ib05
Timeframe	01.05.2026 - 01-05-2026
Targets	Validate DT-enabled resilience assessment for the distribution grid by simulating N-1 contingencies over historical power-flow data. Verify grid stability by iteratively disconnecting network lines and checking that voltage variations stay within the $\pm 7\%$ limit and line loading does not exceed the 80% threshold. Identify and report the critical elements to support smart coordinated planning.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER DT technology provider, with a functionality to simulate optimal power flows and N-1 contingency analysis.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. • Smart meter data (exported and imported power).
Triggering Event	Scheduled or on-demand initiation of N-1 contingency analysis for a defined set of historical scenarios (or periods of stress) to assess the grid's operational limits and bottlenecks.
Pre-condition	• Triggered by the DSO on-demand upon need for N-1 contingency validation for the grid.
Experiment description	Using SCADA records and metering power-flow snapshots from the grid: 1) Combine SCADA and metering data to accurately model the active and reactive power per load for each timestamp. 2) Build the MV power-flow and run a baseline simulation under normal conditions. 3) For every line in the network, simulate an N-1 contingency by setting the line out of service. 4) Run the power-flow and evaluate stability against defined constraints: Non-convergence, Overvoltage, Undervoltage, and Overload. 5) Record all elements that trigger a violation as "critical elements". 6) Generate a report containing the timestamps and the list of critical lines alongside their specific failure reason.
Post-condition	The N-1 contingent characteristic of the grid is evaluated. Critical elements are identified, categorized by violation type, and stored.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Datasets required for the experiment	• Historical SCADA and metering data for MV nodes and lines (12+ months). • MV network topology.
Field data to be gathered	• Number of critical elements identified. • ID of the critical line causing the contingency constraint. • Reason for failure (Not converged, Overvoltage, Undervoltage, Overload). • Timestamp of occurrence.
Related KPIs	Ib05-1: Critical elements identified

Results of the experiment

The study network has been evaluated over a year of historical data, processing intervals combining 5-minute SCADA measurements and hourly meter data. The N-1 contingency analysis algorithm iteratively isolated individual grid lines to evaluate network resilience, temporarily dropping them and checking for convergence, $\pm 7\%$ voltage limits, and a line loading limit of 80%. Resulting in no critical elements identified for this period.

To illustrate how the hosting capacity visualization is produced in ETER, a scenario is first created for a particular moment in the historical record, a forecast, or real-time data, and this scenario serves as the baseline for the hosting capacity calculation.

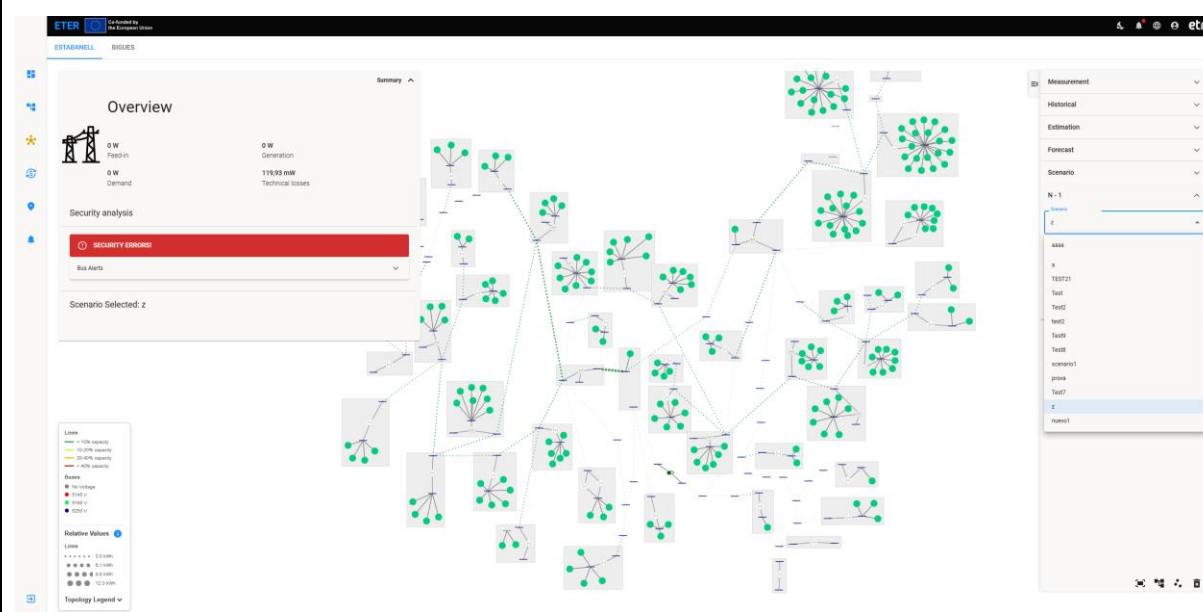


Figure 23. ETER scenario selection.

From this baseline, the N-1 contingency tool is opened, the lines of interest are selected, and the Run action is executed.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

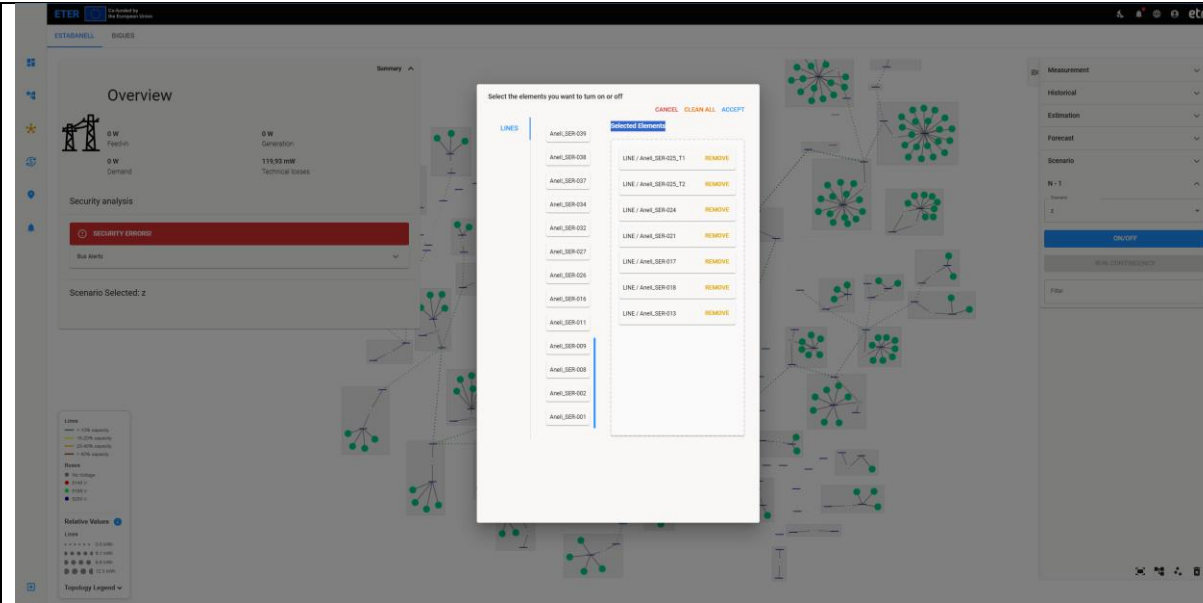


Figure 24. ETER line selection for N-1 contingency analysis calculation.

After a short processing interval, the filter is used to select a specific line, and the interface displays the grid power flow, measurements and situation over the topology itself to check how the loads are redistributed.

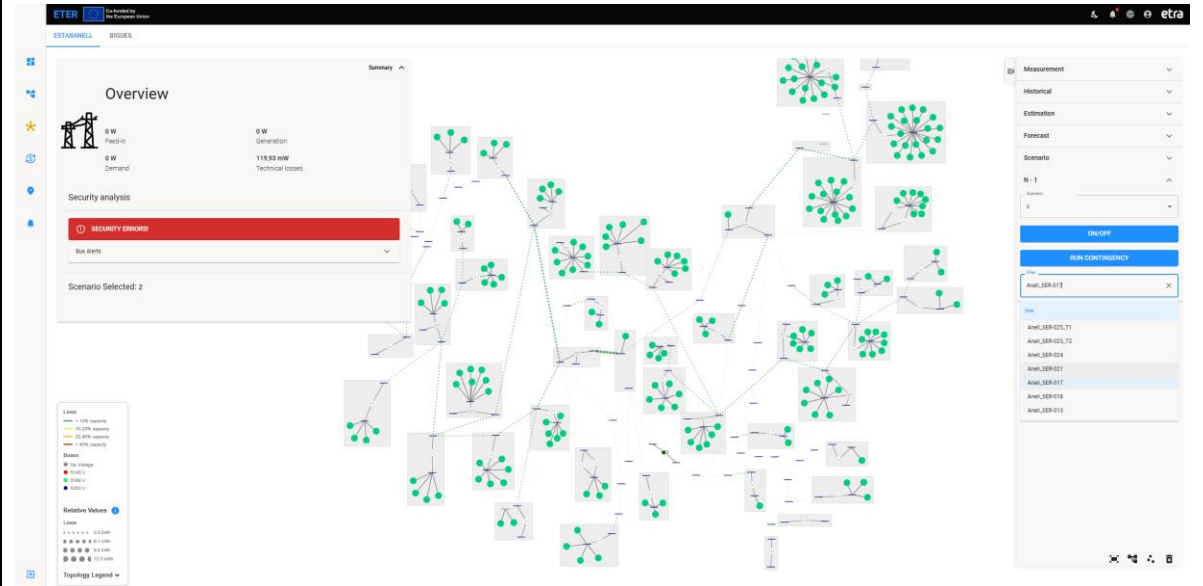


Figure 25. ETER topology status after N-1 scenario selection.

For this Test Case, an offline process has been created to perform the analysis over the historical period. Aggregating the results in case there are problems with some specific lines. The process resulted in no critical elements identified, making the grid N-1 contingent.

Qualitative assessment of the results

In comparison to classic static grid planning models based on peak-load assumptions, calculations based on the DT simulations using high-granularity SCADA and metering data provide a much more realistic and dynamic view of grid stress. This test case has been performed with dynamic

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

calculations over a continuous historical period to identify the specific moments and conditions that make the grid vulnerable.

The idea with this information, and the primary application of this service, is to support scheduled grid maintenance operations. When a specific line needs to be disconnected for several hours, grid operators will use the service to verify that the rest of the network remains N-1 contingent despite the planned outage. This assessment will be performed initially offline using load and generation forecasts to safely plan the maintenance window and subsequently executed with real-time data to continuously monitor and ensure grid stability during the actual maintenance execution.

The associated KPI measuring the grid N-1 capacity is the number of critical elements identified in the systems through the DT simulations:

Table 20. Key Performance Indicator 1 for UC Ib05

KPI ID	Ib05-1
KPI Name	Critical elements identified
Related Use Case	UC Ib05
KPI Description	This KPI measures the absolute number of unique grid elements (e.g., lines) that, when disconnected during the simulation, cause the distribution network to violate operational limits (non-convergence, $\pm 7\%$ voltage limits, or $>80\%$ line loading), thereby making the grid not N-1 contingent.
KPI Formula	$\sum \text{Unique Critical Elements}$
Variables explanation	N/A
Unit of measurement	Number of critical elements
Baseline	n.a.
KPI Value	0
Reference signal(s)	n.a.
Comments	No critical elements are identified by the DT under normal operating conditions. The grid is N-1 contingent.

3.3.4.2 UC Ib06 DT-enabled new RES integration validated plan in the MV grid

The first test case executed (TC Ib06.1) for the demonstration of Use Case Ib06 ran the functionality with historical data for one year.

Table 21. Test case 1 for UC Ib06

Test Case ID	TC Ib06.1
Name	DT-enabled new RES integration validated plan in the MV grid
Related UC	UC Ib06
Timeframe	24.01.2023 – 09.01.2024

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Targets	Validate DT-enabled hosting capacity planning for the MV grid by deriving hosting capacity per substation from historical data, verify voltage variations stay within the 7% limit and line loading constraints, and provide hosting capacity metrics (MW) to support bidirectional power integration planning. The hosting capacity service will be available in ÉTER for scenario analysis.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider, with a functionality to calculate hosting capacity and scenario analysis.
Assets and systems involved	• ÉTER • SCADA (P, Q, V, I) from the nodes. • Smart meter data (exported and imported power).
Triggering Event	On-demand or scheduled initiation of hosting capacity analysis for a defined MV grid scenario using the latest available or historical data.
Pre-condition	• Network topology loaded and validated in ÉTER. • High consumption scenarios historical MV SCADA and meter data available. • Hosting capacity service deployed and integrated. • Converged power-flow Jacobian result prepared for the MV network.
Experiment description	Using hourly and 5-minute power-flow snapshots from a substation: 1) Build MV power-flow and derive Jacobian. 2) Invert the Jacobian to relate active power injections to voltage variations. 3) Assume a linear relation to estimate the maximum active injections/consumptions per bus without exceeding a 7% voltage variation threshold. 4) Compute line current variability with increasing active power to ensure line ratings are not exceeded. 5) Derive per-location hosting capacity for generation and consumption. 7) Perform an analysis on data with historical SCADA and meter data available to assess the variability of the hosting capacity along the year on the specific grid area. 8) Send the information of the most restrictive scenario to the Dataspace connector and PanEU-scenario Hosting Capacity Map
Post-condition	Hosting capacity results (MW) per substation for generation and consumption computed and stored with its limiting element identified (voltage or line). Hosting capacity value available for planning.
Datasets required for the experiment	• Historical SCADA and metering data for MV nodes and lines. • MV network topology.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Field data to be gathered	• Hosting capacity results per substation (MW). • Limiting element (bus or line) causing constraint. • Maximum injection and consumption values per location.
Related KPIs	Ib06-1: Available bidirectional (RES and loads) power hosting capacity

Results of the experiment

The study network comprises 43 substations in the MV grid under analysis. The DT-enabled hosting capacity analysis returned a total hosting capacity of 50.53 MW. For reporting purposes, the minimum out of all the hosting capacities over the high consumption scenarios extracted for each substation.

To illustrate how the hosting capacity visualization is produced in ETER, a scenario is first created for a particular moment in the historical record, a forecast, or real-time data, and this scenario serves as the baseline for the hosting capacity calculation.

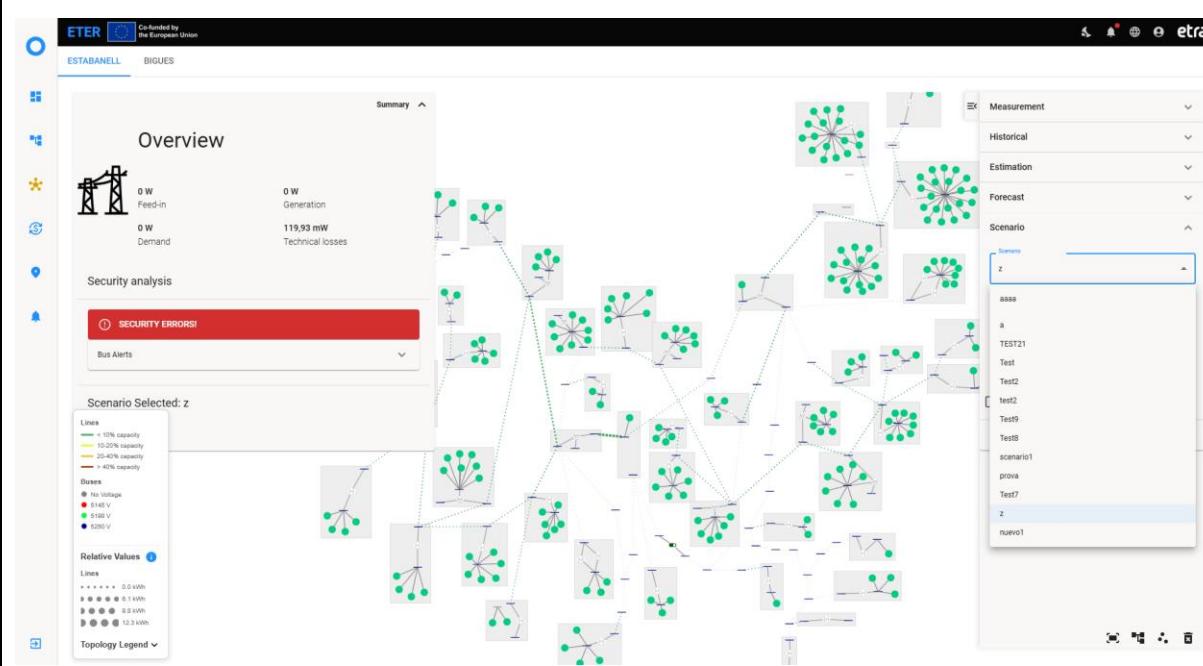


Figure 26. ETER scenario selection.

From this baseline, the hosting capacity tool is opened, the buses/substations of interest are selected, and the Run action is executed.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

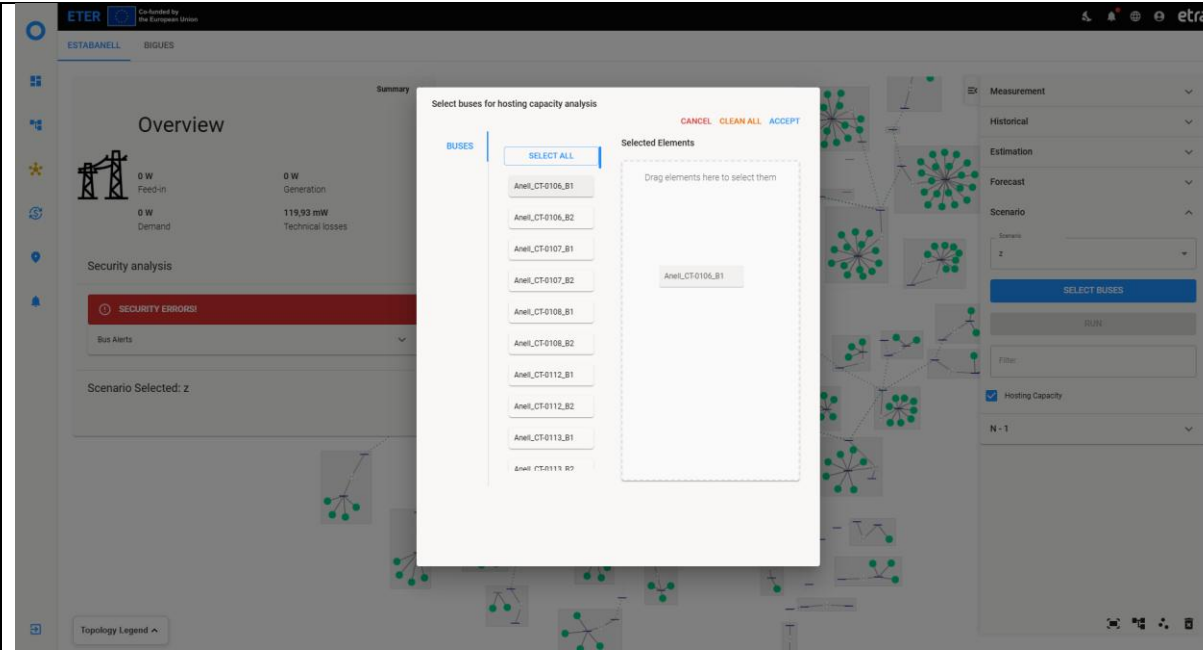


Figure 27. ETER bus/substation selection for hosting capacity calculation.

After a short processing interval, the filter is used to select a specific bus, and the interface displays the hosting capacity in MW, the limiting factor, and the name of that limiting factor for the chosen location.

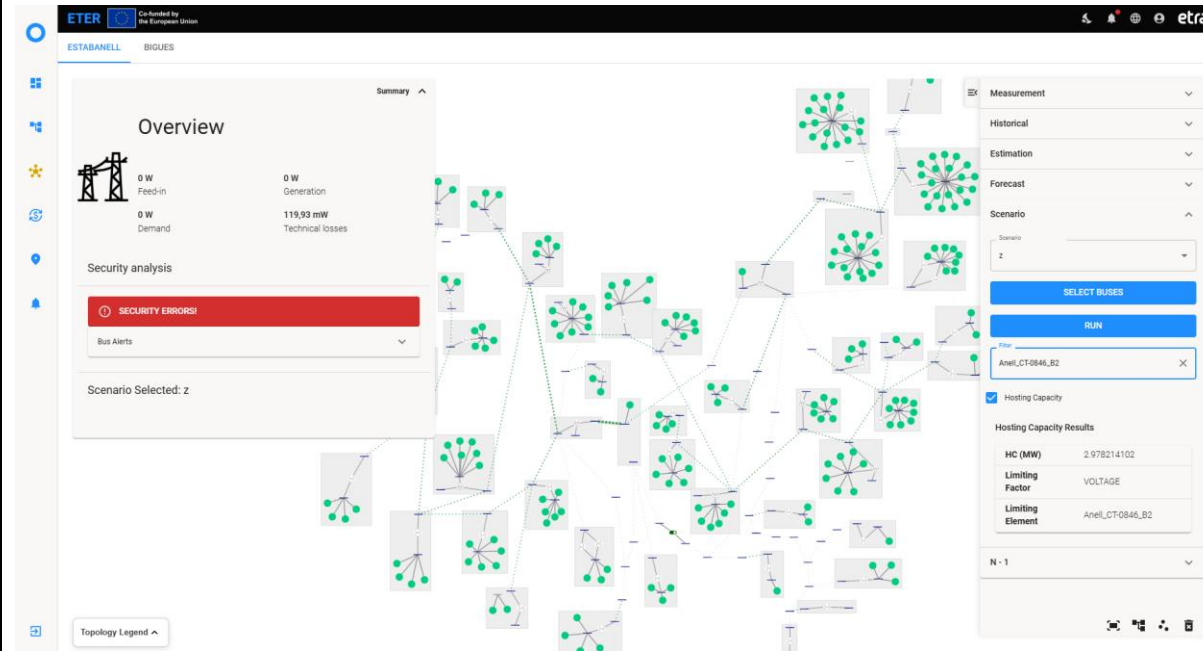


Figure 28. ETER hosting capacity results per bus.

An offline process has been created to perform the same analysis over the peak scenarios period. The results of all hosting capacity calculations across the scenarios are then aggregated by taking the minimum for each substation and are transmitted through the dataspace to the panEU hosting capacity map.

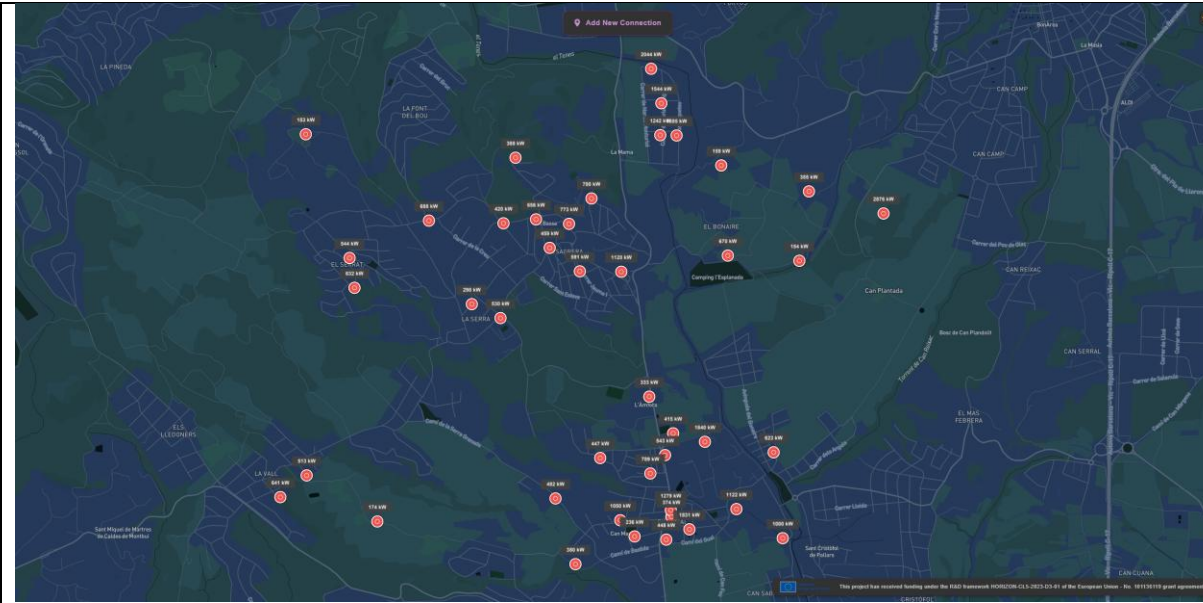


Figure 29. Hosting capacity map with ESTABANELL hosting capacity information.

Calculations over uncertainties related to the linearization approach via the Jacobian have been calculated (<1% difference) and the reliance on historical hourly snapshots. Limitations of the approach are acknowledged, such as the static nature of per-hour analysis and potential data quality issues.

To obtain the hosting capacity results, the Jacobian matrix is derived by linearising the AC power-flow equations around the operating point represented by the selected scenario. It contains the partial derivatives relating active and reactive power variations to changes in voltage angles and voltage magnitudes. Inverting the Jacobian provides the sensitivity relationships between changes in power injections and the resulting network-state variations. In particular, the (dV/dP) component estimates how the voltage magnitude at each bus changes when active power is injected at another bus. These sensitivities are applied to the baseline scenario to estimate the maximum generation or consumption variation that can be accommodated before the defined voltage limits are exceeded. The most restrictive value across all affected buses is selected and then compared with line-current constraints, with the minimum value determining the final hosting capacity for each location.

Ib06-KPI1: The hosting capacity for RES generation was calculated at 50.91 MW, and the hosting capacity for loads was calculated at 68.69 MW.

Qualitative assessment of the results
In comparison to classic hosting capacity calculations methods, based on pre-defined simultaneity factors, calculations based on the DT simulations are more restrictive – i.e., show lower hosting capacity for the studied nodes. This test case has been performed with data from identified scenarios where the grid is significantly stressed. A subsequent test-case is performed with dynamic calculations for the whole year based on the DTs forecasting services.

The second test case executed (TC Ib06.2) for the demonstration of Use Case Ib06 ran the functionality in cooperation with the DT module to assess the validated plans toward future scenarios.

Table 22. Test case 2 for UC Ib06

Test Case ID	TC Ib06.2
Name	DT-enabled new RES integration validated plan in the MV grid
Related UC	UC Ib06
Timeframe	01.05.2026 - 01-05-2026
Targets	Validate DT-enabled hosting capacity planning for the MV grid by deriving hosting capacity per substation from historical data, verify voltage variations stay within the 7% limit and line loading constraints, and provide hosting capacity metrics (MW) to support bidirectional power integration planning. The hosting capacity service will be available in ETER for scenario analysis.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider, with a functionality to calculate hosting capacity and scenario analysis.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. • Smart meter data (exported and imported power).
Triggering Event	On-demand or scheduled initiation of hosting capacity analysis for a defined MV grid scenario using the latest available or historical data.
Pre-condition	• Network topology loaded and validated in ÉTER. • 12 months of historical MV SCADA and meter data available. • Hosting capacity service deployed and integrated. • Converged power-flow Jacobian result prepared for the MV network.
Experiment description	Using hourly and 5-minute power-flow snapshots from a substation: 1) Build MV power-flow and derive Jacobian. 2) Invert the Jacobian to relate active power injections to voltage variations. 3) Assume a linear relation to estimate the maximum active injections/consumptions per bus without exceeding a 7% voltage variation threshold. 4) Compute line current variability with increasing active power to ensure line ratings are not exceeded. 5) Derive per-location hosting capacity for generation and consumption. 7) Perform an analysis on data with historical SCADA and meter data available to assess the variability of the hosting capacity along the year on the specific grid area. 8) Send the information of the most restrictive scenario to the Dataspace connector and PanEU-scenario Hosting Capacity Map

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Post-condition	Hosting capacity results (MW) per substation for generation and consumption computed and stored with its limiting element identified (voltage or line). Hosting capacity value available for planning.
Datasets required for the experiment	- Historical SCADA and metering data for MV nodes and lines (12+ months). - MV network topology.
Field data to be gathered	- Hosting capacity results per substation (MW). - Limiting element (bus or line) causing constraint. - Maximum injection and consumption values per location.
Related KPIs	Ib06-1: Available bidirectional (RES and loads) power hosting capacity

Results of the experiment

The study network comprises 43 substations in the MV grid under analysis. The DT-enabled hosting capacity analysis returned a total hosting capacity of 50.53 MW. For reporting purposes, the minimum out of all the hosting capacities across the year extracted for each substation.

To illustrate how the hosting capacity visualization is produced in ETER, a scenario is first created for a particular moment in the historical record, a forecast, or real-time data, and this scenario serves as the baseline for the hosting capacity calculation.

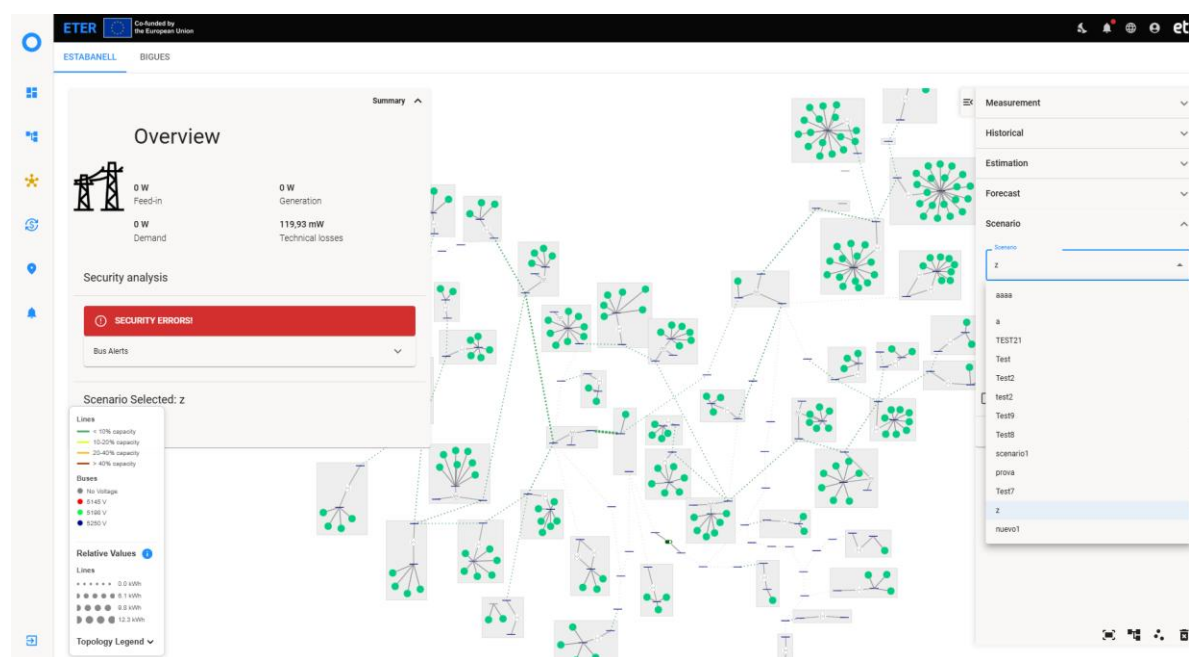


Figure 30. ETER scenario selection.

From this baseline, the hosting capacity tool is opened, the buses/substations of interest are selected, and the Run action is executed.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

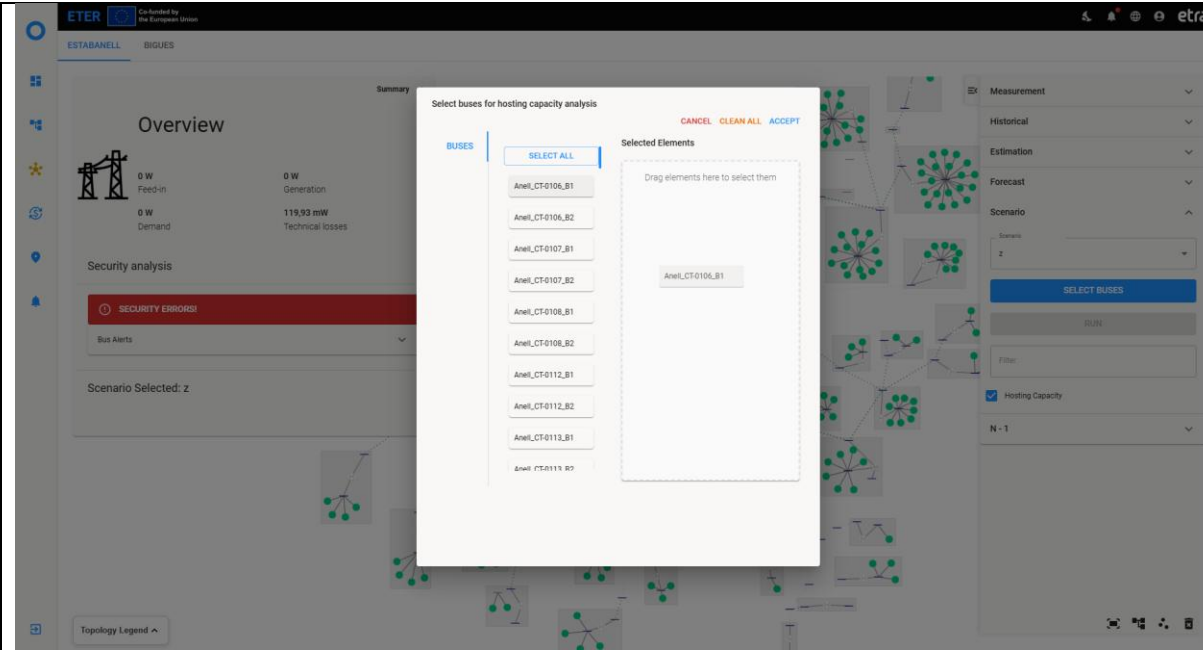


Figure 31. ETER bus/substation selection for hosting capacity calculation.

After a short processing interval, the filter is used to select a specific bus, and the interface displays the hosting capacity in MW, the limiting factor, and the name of that limiting factor for the chosen location.

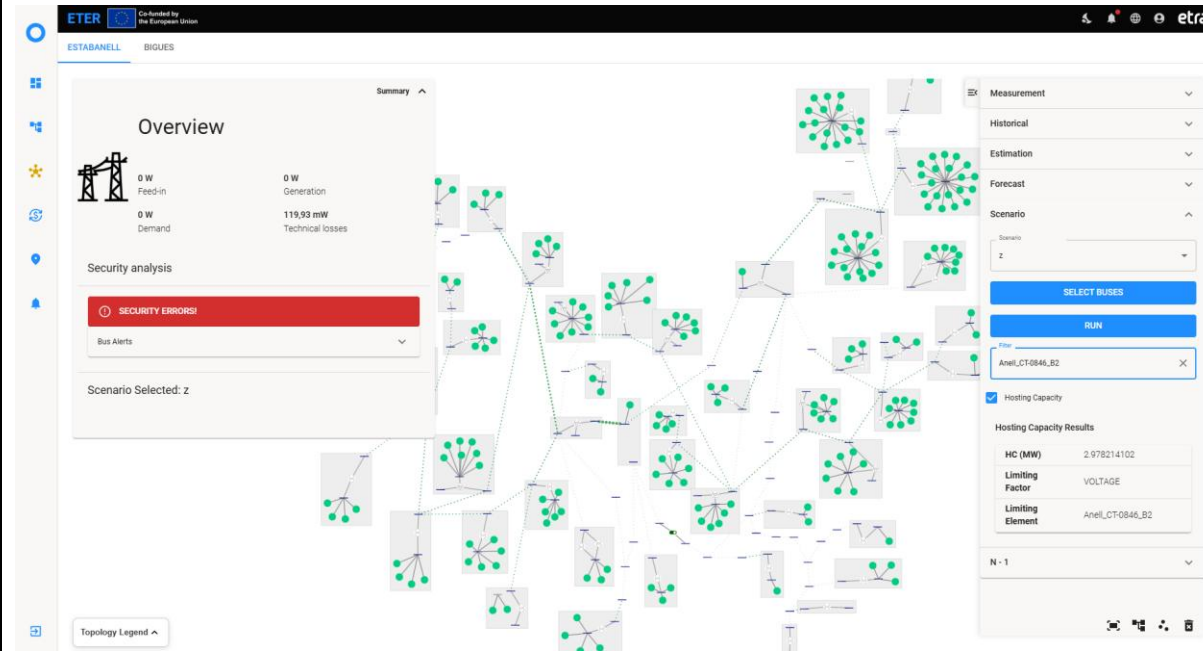


Figure 32. ETER hosting capacity results per bus.

An offline process has been created to perform the same analysis over the historical period. The results of all hosting capacity calculations across the year are then aggregated by taking the minimum for each substation and are transmitted through the dataspace to the panEU hosting capacity map.

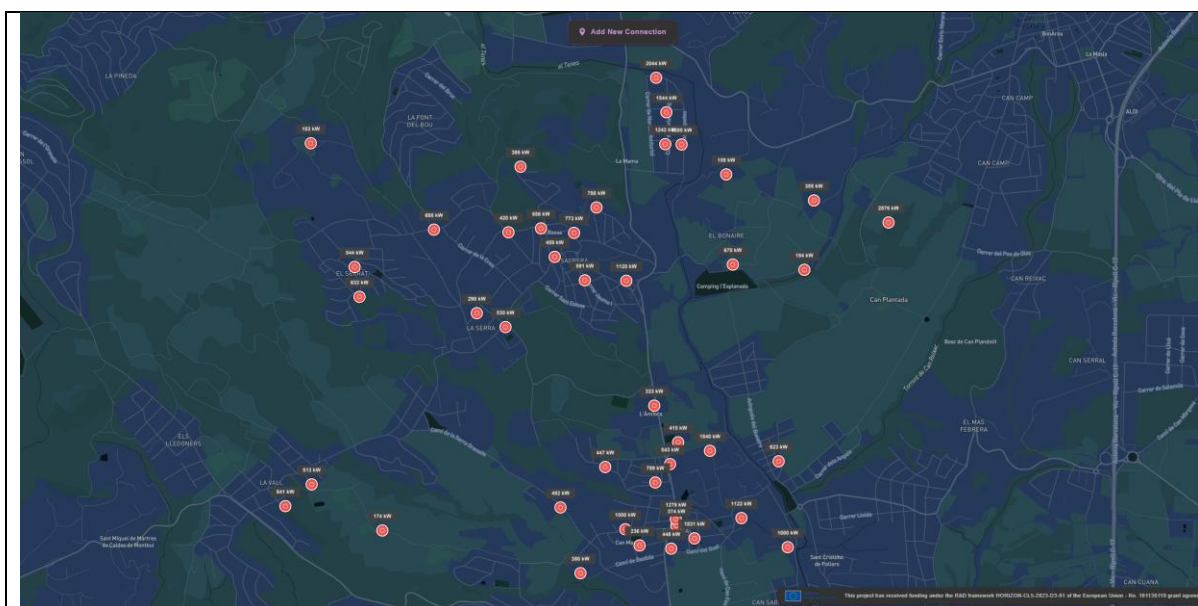


Figure 33. Hosting capacity map with ANELL hosting capacity information.

Calculations over uncertainties related to the linearization approach via the Jacobian have been calculated and the difference is less than one percent. Concluding that this approach is viable for hosting capacity calculations.

Ib06-KPI1: The hosting capacity for RES generation was calculated at 50.53 MW, and the hosting capacity for loads was calculated at 67.15 MW.

Qualitative assessment of the results

In comparison to classic hosting capacity calculations methods, based on pre-defined simultaneity factors, calculations based on the DT simulations are more restrictive – i.e., show lower hosting capacity for the studied nodes. This test case has been performed with dynamic calculations for the whole year.

The idea with this information is to analyse and perform some analytics over the variation of the hosting capacity values over the year, to serve as a starting point for the Test Case TC Ib14-1 for participating in Local Flexibility Markets through flexible connections.

Table 23. Key Performance Indicator 1 for UC Ib06

KPI ID	Ib06-KPI1
KPI Name	Available bidirectional (RES and loads) power hosting capacity
Related Use Case	UC Ib06
KPI Description	This KPI measures the increased RES and load available power capacity that could be deployed along the grid thanks to the simulations implemented by the DSO's DT.
KPI Formula	$\sum_{n=1}^N \min(hc_{RES}(MW)_n, hc_{load}(MW)_n)$
Variables explanation	N, total number of buses/substations to calculate hosting capacity.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

	$hc_{RES}(MW)_n$, generation hosting capacity calculated for the bus/substation n in megawatts. $hc_{load}(MW)_n$, load hosting capacity calculated for the bus/substation n in megawatts.
Unit of measurement	Megawatts (MW)
KPI value	50.53 MW
Baseline	n.a.
Reference signal(s)	n.a.
Comments	n.a.

3.3.4.3 UC Ib07 DT-based grid maintenance planning and N-1 assessment

The table below presents the execution of the experiment (test cases) that demonstrates UC Ib07, where the N-k contingency analysis has been run dynamically by the DT. All test cases for short, medium and long-term forecasting horizons upon expected maintenance activities in the distribution grid can be seen in Annex B.

Table 24. Test case 1 for UC Ib07

Test Case ID	TC Ib07.1
Name	DT-based grid maintenance planning and N-1 assessment
Related UC	UC Ib07
Timeframe	15/04/2026 8:00h - 16/04/2026 13:00h
Targets	Validate the Digital Twin (ETER) for planning grid maintenance activities (e.g., line disconnection for concrete pole installation). Perform load and generation forecasts for the outage period and execute N-1 contingency analysis to ensure the grid remains resilient during the maintenance. Calculate the accuracy of the DT predictions compared to real-world data using MAPE.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider, with a functionality to simulate forecasts, optimal power flows and N-1 contingency analysis.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. • Smart meter data (exported and imported power).
Triggering Event	Scheduled maintenance for concrete pole replacement online SER-002
Pre-condition	• Network topology loaded and validated in ÉTER. • Forecasting and N-1 Contingency services deployed and integrated within the DT. • Real-time SCADA and concentrator data streams active.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Experiment description	1) Identify the line SER-002 to be disconnected over the maintenance timeframe 15/04/2026 08h to 16/04/2026 13h. 2) Generate forecasts in ETER for the maintenance window. 3) Run power-flow simulations for these forecast hours with the specific line out of service to identify potential issues. 4) Perform N-1 contingency analysis on the remaining network to ensure security of supply if another fault occurs during maintenance. 5) Save the forecasted power flow states. 6) Once maintenance occurs, gather real-time data. 7) Compare forecasted vs. real values.
Post-condition	Maintenance viability is validated. The grid is verified to be N-1 contingent during the outage. Forecast accuracy (MAPE) is calculated and stored.
Datasets required for the experiment	• MV network topology. • Forecasted load and generation profiles. • Real-time SCADA and metering data recorded during the actual maintenance activity.
Field data to be gathered	• Forecasted power flow values (P, Q, V, I). • Real-time power flow values. • MAPE (Mean Absolute Percentage Error) of the deviation. • List of operational violations (if any) during simulation.
Related KPIs	lb07-KPI1: Accuracy in recalculated power flows.
Results of the experiment	
The experiment focused on a real maintenance operation: the replacement of a concrete pole on line SER-002, which required a scheduled outage from April 15th, 2026 (08:00) to April 16th, 2026 (13:00) The ETER tool allowed for a detailed simulation of this disconnection: • Forecast Generation: Using the Forecast tab, a slider was used to select the specific hour to perform forecast, see Figure 34.	

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning



Figure 34. ETER GUI, forecast tab. SER-002.

- **Scenario Creation:** A specific scenario was created where the line SER-002 was disconnected by closing its respective switches in the Digital Twin interface, see Figure 35.

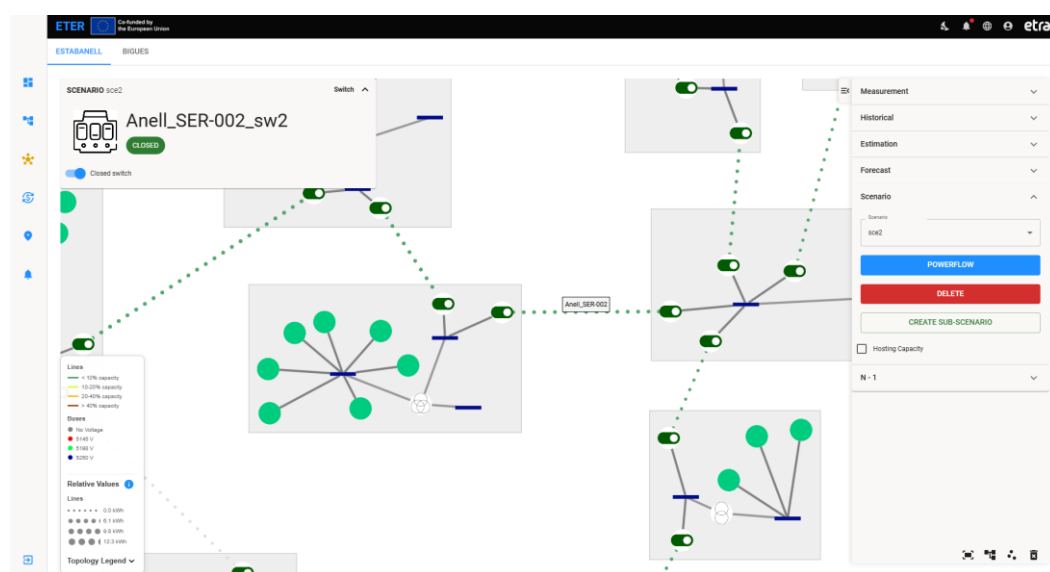


Figure 35. ETER GUI, scenario switch closure. SER-002.

The scenario was then updated to analyse the resulting grid state and power flow redistribution, see Figure 36.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

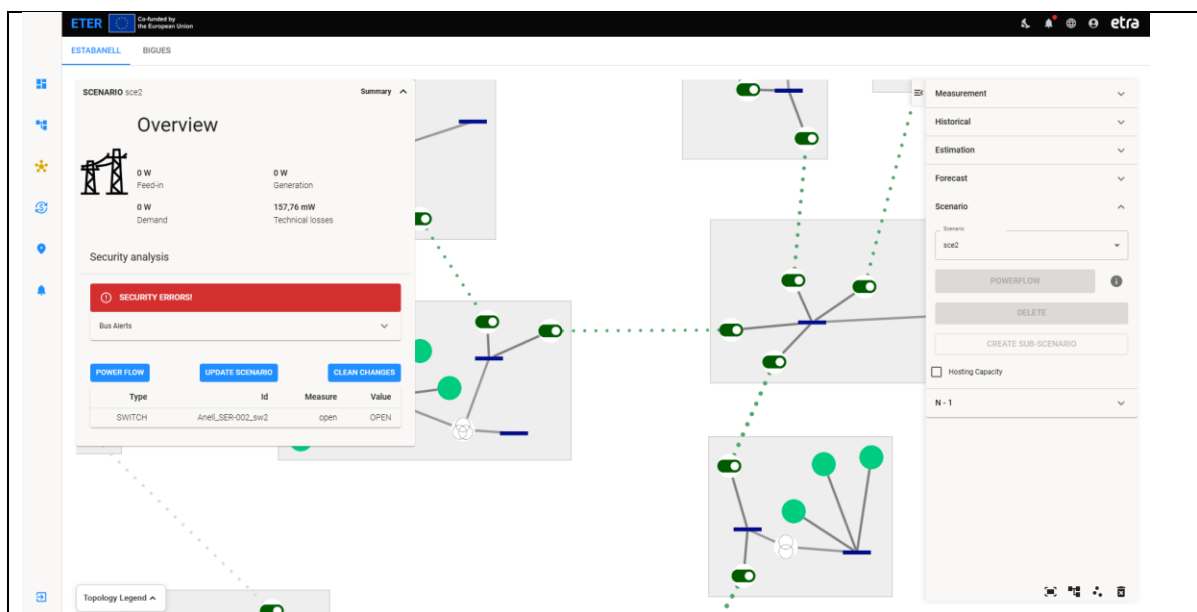


Figure 36. ETER GUI, scenario update with new changes. SER-002.

- **N-1 Security Analysis:** This outage scenario was loaded into the N-1 Contingency Analysis module to verify that the grid remained resilient if a second line were to fail during the works, see Figure 37.

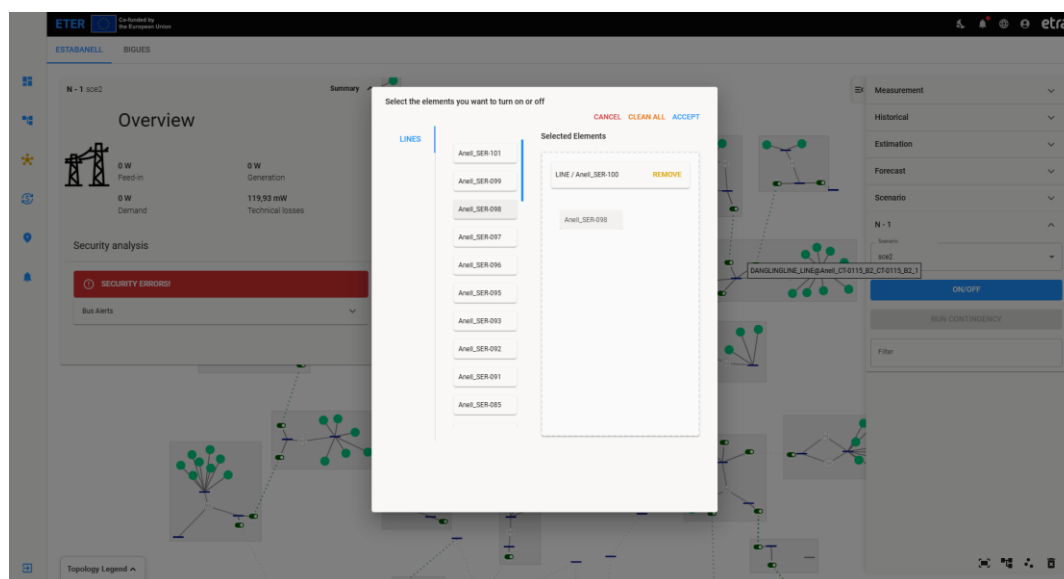


Figure 37. ETER GUI, N-1 Contingency Analysis module. SER-002.

ETER generated sub-scenarios for every tested line to visualize the grid status after each potential second contingency, see Figure 38.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning



Figure 38. ETER GUI, N-1 Contingency Analysis subscenarios. SER-002.

An offline process executed the N-1 study for every hour of the forecast window, see Figure 39, finding no operational violations or security issues for the planned maintenance.

An offline process executed the N-1 study for every hour of the forecast window for each substation, see Figure 39 and Figure 40 as examples, finding no operational violations or security issues for the planned maintenance.

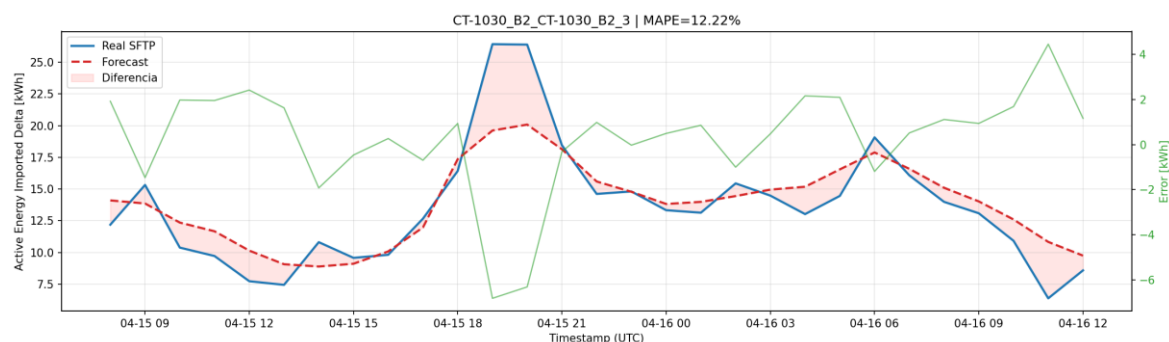


Figure 39. Forecast evolution of the different substations during maintenance.

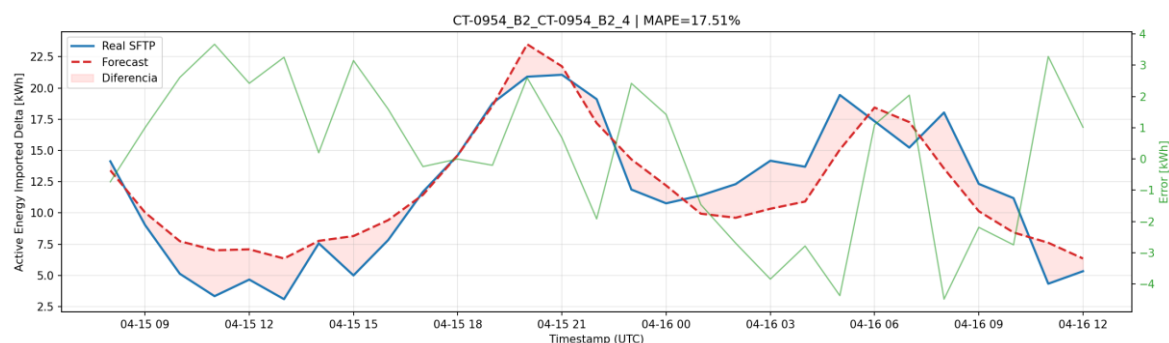


Figure 40. Forecast evolution of substation CT-0954 during maintenance.

During the actual work, a real-time process was used to monitor the grid. Because SCADA visibility is limited to specific substations, the system combined forecasts, SCADA data, and concentrator

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

data to perform a continuous State Estimation and N-1 analysis, ensuring no power flow or stability problems occurred.

Finally, the real data from the concentrators was compared to the hourly predicted active power at each substation. As this is a regression problem, the accuracy was measured using MAPE (Mean Absolute Percentage Error), resulting in an average MAPE of X% for the recalculated power flows considering 43 substations.

Qualitative assessment of the results

The test case successfully validated the ETER Digital Twin (DT) as a reliable tool for planning grid maintenance activities, specifically for the disconnection of line SER-002 to replace a concrete pole. The DT demonstrated its capacity to integrate load and generation forecasts, simulate power flow redistribution under outage conditions, and perform comprehensive N-1 contingency analysis to ensure grid resilience throughout the maintenance window.

The system successfully generated hourly forecasts for active power at 43 substations over the entire maintenance period, which were visualized through the ETER interface. This allowed operators to anticipate grid behaviour before the physical disconnection occurred and make informed decisions about the feasibility of the planned outage.

Scenario simulation was another key capability demonstrated during the test. By closing the switches associated with line SER-002 in the DT interface, a realistic outage scenario was created that accurately reflected the intended maintenance activity. The system automatically recalculated power flows and updated the grid state to reflect the new topology, confirming that no operational violations such as overloads or voltage violations would arise from the planned maintenance.

The N-1 contingency analysis provided an additional layer of security validation for the maintenance planning process. The DT executed an offline N-1 study for every hour of the forecast window across all substations, systematically evaluating the impact of each credible single contingency. This analysis verified that even if an additional line/substation failed during the maintenance works, the grid would remain secure and stable, with no security issues detected throughout the entire maintenance period.

Prediction accuracy was evaluated by comparing forecasted versus real concentrator data collected during the actual maintenance activity. Using Mean Absolute Percentage Error (MAPE) as the metric for this regression problem, the average MAPE across 43 substations was 13.53%. This indicates a reasonably accurate predictive performance for planning purposes.

The test case confirmed that the ETER Digital Twin can create "what-if" scenarios that incorporate forecasted load and generation profiles, enabling proactive planning of maintenance activities with confidence. Operators can simulate switch operations to model line/substation disconnections and immediately observe the impact on power flows and grid stability, while the automated N-1 module evaluates all credible contingencies for each hour of the forecast window.

3.3.4.4 UC Ib14 Local Flexibility Market-enabled Flexible Connection Agreements

Several transactions were executed during the demo period to validate the functionalities across different days. One single test case is reported, but a table (Table 27) with all the experiments executed has been included with all the details of the different transactions.

Table 25. Test case 1 for UC Ib14

Test Case ID	TC Ib14.1
Name	Local Flexibility Market-enabled Flexible Connection Agreements
Related UC	UC Ib14
Timeframe	June – September 2026
Targets	Allow the temporary increase of contracted power limits (implementation of Flexible Contract Agreements – FCAs) in the local distribution network through a validation with the Digital Twin (ETER). Upon a settled Peer-to-Peer (P2P) market transaction related to FCAs, the DSO validates that the energy to be exchanged does not compromise the operation of the grid by running long and short-term hosting capacity calculations.
Actors involved	• ANELL – Distribution System Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider of the DT that validates the suitability of the scenario. • OMIE as P2P Local Flexibility Market (LFM) operators. • LFM participants.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. • Smart meter data (exported and imported power). • OMIE's Local Trading System (LTS) as LFM platform.
Triggering Event	A P2P market transaction related to a FCA option in the LFM is settled. The DSO needs to validate that the transaction can be executed for the requested period.
Pre-condition	n.a.
Experiment description	1) The DSO is notified when a transaction is matched (for the purpose of the demonstrations this step is manual, but it could be automatised) 2) ÉTER generates a scenario for the day and hour of the expected transaction with forecasting data. 3) Run power-flow simulations for these forecast hours with the specific positions of the participating market actors to identify potential issues. 4) ÉTER stores the forecasted power flow scenarios. 5) OMIE acts as a neutral Local Flexibility Market Operator, providing the market infrastructure required.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Post-condition	Transactions in the P2P market for FCA executions are validated.
Datasets required for the experiment	- MV network topology. - Forecasted load and generation profiles. - Real-time SCADA and metering data recorded during the actual maintenance activity. - Quantity of power per session and unit of the proposed transactions.
Field data to be gathered	- Forecasted power flow values (P, Q, V, I). - Real-time power flow values.
Related KPIs	Ib14-KPI1: Number of LFM sessions opened. Ib14-KPI2: Increased bidirectional (RES and loads) power hosting capacity.

Results of the experiment

The test cases to demonstrate UC Ib14 were executed from June to September 2026 (M29 to M33). To simplify the reporting process, the results of the experiments are synthetised below into explaining the whole process with graphic support, and a descriptive table is included with the information of all the P2P exchanges that were simulated and analysed with the DT.

First, the offers are introduced into the P2P LFM by actors willing to extend their contracted power limits (according to the cases defined in eventual Flexible Connection Agreements – FCAs) signed with the DSO and the retailer (see Figure 41)

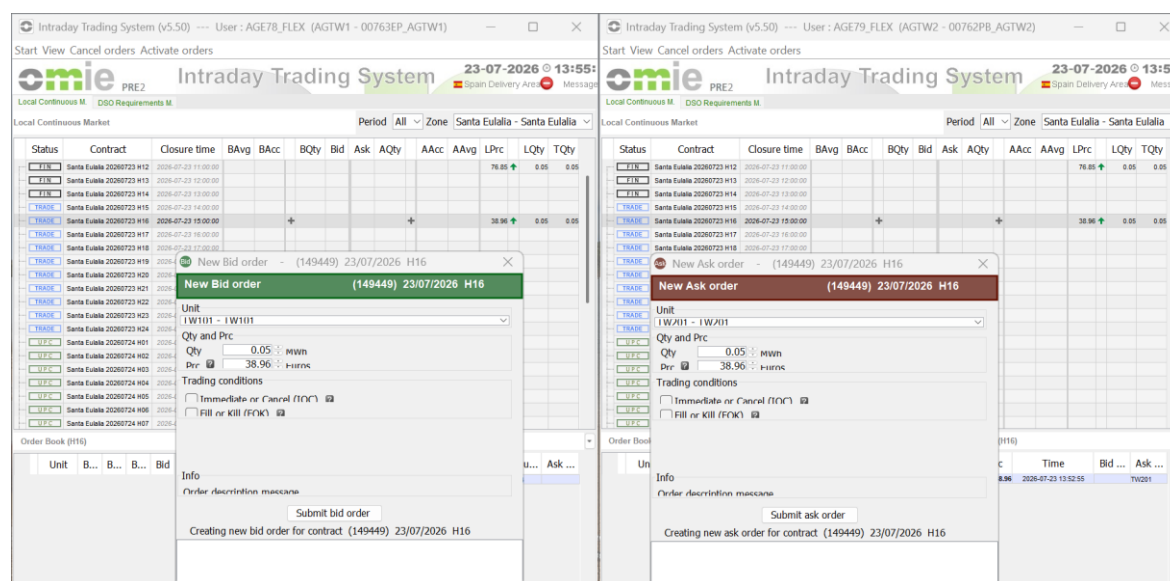


Figure 41. P2P offers in the Local Trading System (based on XBID)

For simplicity, as these markets are not yet operational in the Iberian electricity systems, and thus, some detailed are still under definition, the price for all transactions has been established as the average pool price for that hour.

When two offers match, the transaction is automatically executed (see Figure 42).



Figure 42. Matched offers notification

Once that happens, the DSO must always be notified for the DT to run the simulations and validate that the proposed transaction can be executed (i.e., that the proposed transaction is within the hosting capacity limits for the clearing period and that it will not cause any disruption in the grid's normal operations).

The DSO uses ÉTER to create a scenario for the specific hour of the transaction, starting by validating the grid is per se secure for that moment (see Figure 43)

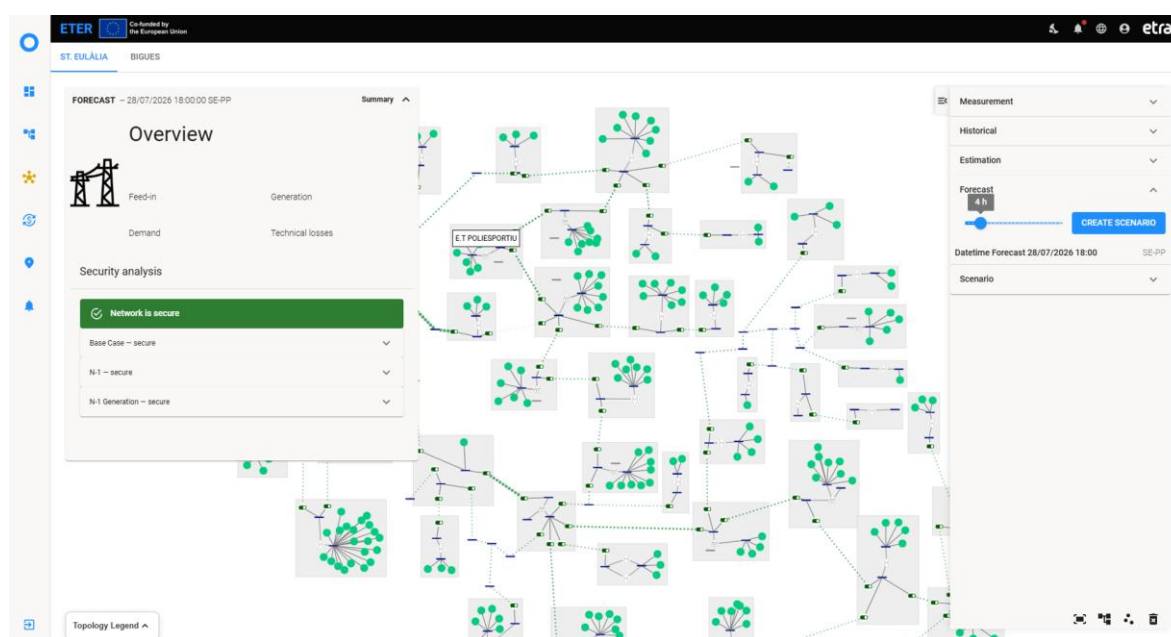


Figure 43. Scenario creation in ÉTER

Then, the scenario is selected for adding the simulation parameters (the specific amounts of power to be exchanged among peers) (see Figure 44).

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

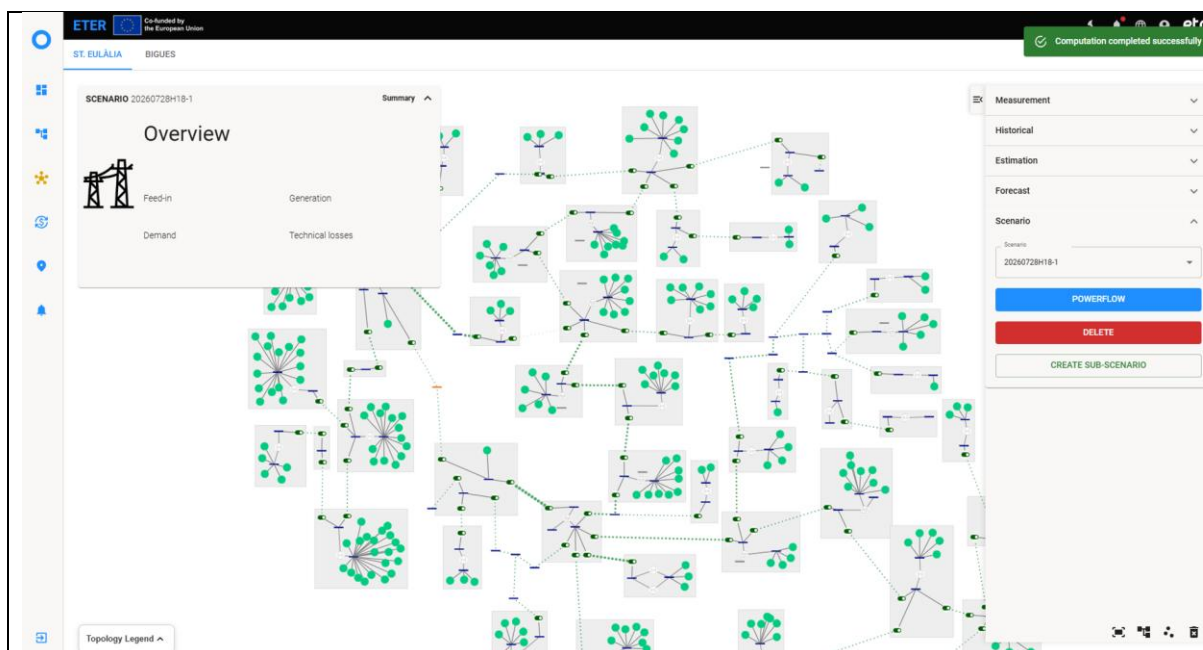


Figure 44. Scenario selection for parameterising the transaction.

After that, the details of the transaction (power and node) are introduced (see Figure 45) into the scenario, running the power flow calculations and updating it so that it is stored in the DT data base.

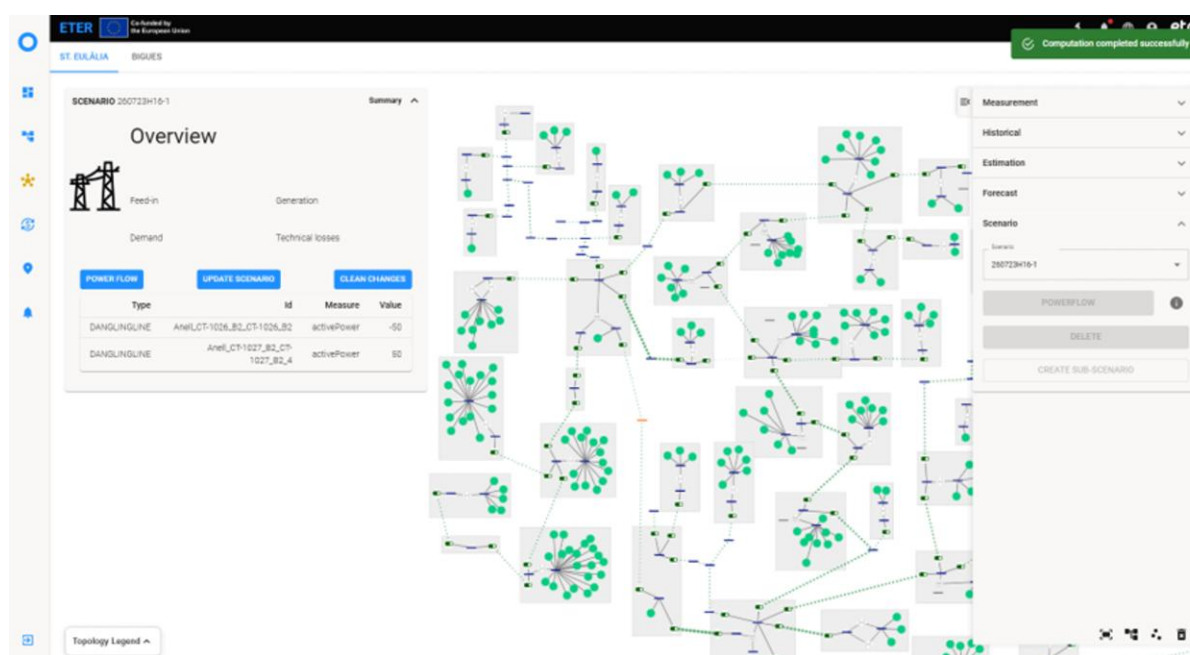


Figure 45. Scenario parameters introduces, power flow ran and scenario updated and stored in ÉTER.

In the case of a scenario with multiple transaction (more than two expected participants) the market positions (power) of all actors are to be introduced one single scenario. This validates the coexistence of all power exchanged in the grid (see Figure 46).

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

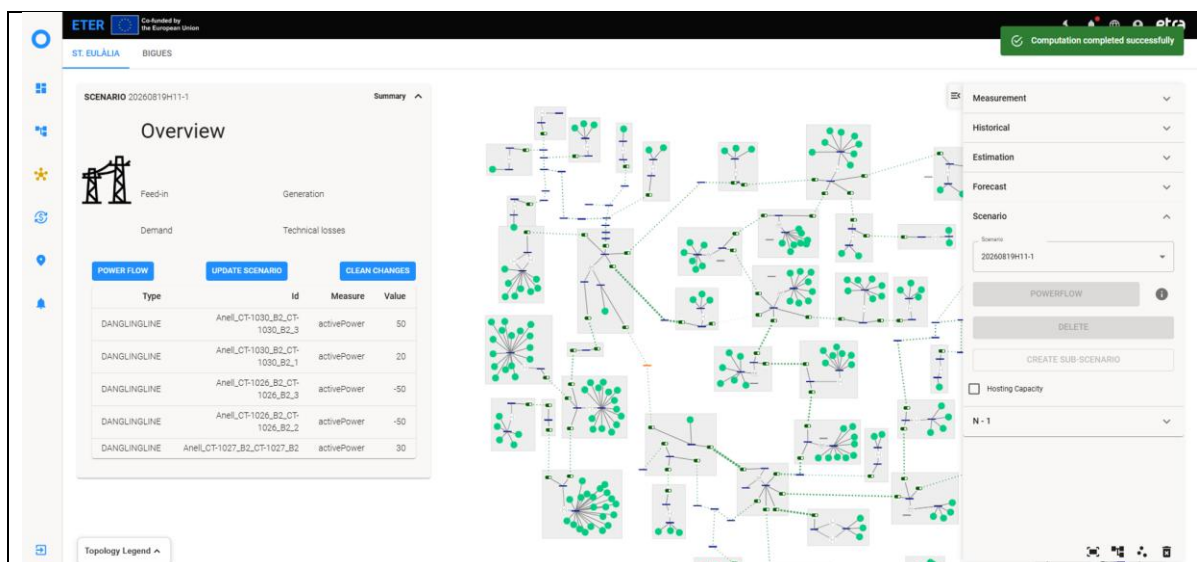


Figure 46. Scenario simulation with multiple transactions.

ÉTER stores all scenarios for re-visiting them if needed and/or for updating them if new transactions are expected in the same period in which a scenario was already validated (see Figure 47).



Figure 47. Validated scenarios consultation.

For the demonstration activities, a number of industrial users whose activity (either on the consumption or on the generation side) could be subject to benefiting from FCA were identified (see Table 26). Their current limits in contracted power were also used to simulated eventual needs and and/or capacity for extending them.

The demonstrations were limited to the zone of Santa Eulàlia, leaving Bigues for the demonstration activities in WP5.

For internal tracking purposes (and although all transactions are both stored in the LFM's LTS as well as on the simulation scenarios in the DT in ÉTER), all transactions are registered following a specific set of input data, which includes: Direction (Ask offers for generation and Bid offers for consumption), the participating Unit, the Quantity (Qty) in MWh, the Price (Prc) (€), the date of the transaction as well as the hour / session, the day of the week and the contractual period associated to that hour, the zone (limited to Santa Eulàlia), the Agent (there is one for all generation actors

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

and one for all consumption actors), the reference of the DT simulation scenario so that it can be revisited and the Substation where the participant is connected. Additionally, a colour code was followed for offers were not accepted (highlighted in red), and offers that were actually matched (highlighted in green).

Table 26. Selected participants

FSP ID	Agent	Zone	Substation	P1 (kW)	P2 (kW)	P3 (kW)	P4 (kW)	P5 (kW)	P6 (kW)
123653 - TW202 (G)	AGE79 (generation)	Santa Eulàlia de Ronçana	ER-1026 E.R. GAFA	80	80	80	80	80	80
110295 - TW201 (G)	AGE79 (generation)	Santa Eulàlia de Ronçana	ER-1026 E.R. GAFA	50	70	70	70	70	80
115615 - TW101 (C)	AGE78 (consumption)	Santa Eulàlia de Ronçana	ER-1030 E.R. SANTA EULALIA	100	100	100	100	100	125
96460 - TW105 (C)	AGE78 (consumption)	Santa Eulàlia de Ronçana	ER-1030 E.R. SANTA EULALIA	150	150	150	150	150	150
133106 - TW104 (C)	AGE78 (consumption)	Santa Eulàlia de Ronçana	ER-1027 E.R. XENA	70	80	80	80	80	139
74824 - TW204 (G)	AGE79 (generation)	Bigues i Riells del Fai	ER-1033 E.R. BIGUES	232	232	232	232	232	300
130634 - TW203 (G)	AGE79 (generation)	Bigues i Riells del Fai	ER-1033 E.R. BIGUES	300	300	300	300	300	500
129653 - TW103 (C)	AGE78 (consumption)	Bigues i Riells del Fai	ER-1033 E.R. BIGUES	250	250	250	250	250	451
117316 - TW102 (C)	AGE78 (consumption)	Bigues i Riells del Fai (phys	ER-1027 E.R. XENA	346	346	346	346	346	346

As mentioned at the beginning to this results sections, for simplicity purposes, screenshots of all scenarios tested are not to be displayed, but the full tracking of transactions executed and/or validated is depicted below.

Table 27. Executed transactions during for the validation of the DSO's DT as use case enabler in UC Ib14

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Direction	Unit	Quantity (Qty) (MWh)	Price (Prc) (€)	Trading conditions	Date	Hour / session	Day (week)	Periodo contractual	Zona	Agent	DT simulation scenario	Substation
Ask (generation)	123653 - TW202 (G)	0,08	139,47	Immediate or Cancel (IOC)	09/07/2026	H9	Tuesday	P1	Santa Eulàlia de Ronçana	AGE79 (generation)	Test	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	139,47	Fill or Kill (FOK)	09/07/2026	H9	Tuesday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	Test	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	139,47	Fill or Kill (FOK)	09/07/2026	H9	Tuesday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	Test	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,05	138,24	Immediate or Cancel (IOC)	14/07/2026	H9	Tuesday	P1	Santa Eulàlia de Ronçana	AGE79 (generation)	Test	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	138,24	Immediate or Cancel (IOC)	14/07/2026	H9	Tuesday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	Test	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,05	97,88	-	15/07/2026	H12	Tuesday	P1	Santa Eulàlia de Ronçana	AGE79 (generation)	Test	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	97,88	-	15/07/2026	H12	Tuesday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	Test	ER-1030 E.R. SANTA EULALIA
Ask (generation)	123653 - TW202 (G)	0,04	66,25	-	15/07/2026	H15	Tuesday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	Test	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,02	66,25	-	15/07/2026	H15	Tuesday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	Test	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,02	66,25	-	15/07/2026	H15	Tuesday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	Test	ER-1027 E.R. XENA
Ask (generation)	123653 - TW202 (G)	0,04	97,63	-	20/07/2026	H11	Monday	P1	Santa Eulàlia de Ronçana	AGE79 (generation)	260720H11-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,02	97,63	-	20/07/2026	H11	Monday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	260720H11-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,02	97,63	-	20/07/2026	H11	Monday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	260720H11-1	ER-1027 E.R. XENA
Ask (generation)	123653 - TW202 (G)	0,05	76,85	-	23/07/2026	H12	Thursday	P1	Santa Eulàlia de Ronçana	AGE79 (generation)	260723H12-1	ER-1026 E.R. GAFA
Bid (consumption)	133106 - TW104 (C)	0,05	76,85	-	23/07/2026	H12	Thursday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	260723H12-1	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,05	38,96	-	23/07/2026	H16	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	260723H16-1	ER-1026 E.R. GAFA
Bid (consumption)	133106 - TW104 (C)	0,05	38,96	-	23/07/2026	H16	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	260723H16-1	ER-1027 E.R. XENA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Ask (generation)	110295 - TW201 (G)	0,04	81,00	-	28/07/2026	H18	Tuesday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260728H18-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,06	81,00	-	28/07/2026	H18	Tuesday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260728H18-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	81,00	-	28/07/2026	H18	Tuesday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260728H18-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,05	81,00	-	28/07/2026	H18	Tuesday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260728H18-1	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,04	109,48	-	28/07/2026	H19	Tuesday	P1	Santa Eulàlia de Ronçana	AGE79 (generation)	20260728H19-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,06	109,48	-	28/07/2026	H19	Tuesday	P1	Santa Eulàlia de Ronçana	AGE79 (generation)	20260728H19-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	109,48	-	28/07/2026	H19	Tuesday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260728H19-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,05	109,48	-	28/07/2026	H19	Tuesday	P1	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260728H19-1	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,07	23,65	-	30/07/2026	H15	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H15-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,03	23,65	-	30/07/2026	H15	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H15-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,04	23,65	-	30/07/2026	H15	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H15-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,06	23,65	-	30/07/2026	H15	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H15-1	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,07	29,00	-	30/07/2026	H16	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H16-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,03	29,00	-	30/07/2026	H16	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H16-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,04	29,00	-	30/07/2026	H16	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H16-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,06	29,00	-	30/07/2026	H16	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H16-1	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,06	72,05	-	30/07/2026	H17	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H17-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,02	72,05	-	30/07/2026	H17	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H17-1	ER-1026 E.R. GAFA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Bid (consumption)	115615 - TW101 (C)	0,04	72,05	-	30/07/2026	H17	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H17-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	72,05	-	30/07/2026	H17	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H17-1	ER-1027 E.R. XENA
Bid (consumption)	133106 - TW104 (C)	0,02	72,05	-	30/07/2026	H17	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H17-1	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,04	100,09	-	30/07/2026	H18	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H18-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,01	100,09	-	30/07/2026	H18	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H18-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,04	100,09	-	30/07/2026	H18	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H18-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,01	100,09	-	30/07/2026	H18	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H18-1	ER-1027 E.R. XENA
Bid (consumption)	133106 - TW104 (C)	0,05	100,09	-	30/07/2026	H18	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H18-1	ER-1027 E.R. XENA
Ask (generation)	110295 - TW201 (G)	0,02	130,45	-	30/07/2026	H19	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H19-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0	130,45	-	30/07/2026	H19	Thursday	P2	Santa Eulàlia de Ronçana	AGE79 (generation)	20260730H19-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,02	130,45	-	30/07/2026	H19	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H19-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	115615 - TW101 (C)	0,06	130,45	-	30/07/2026	H19	Thursday	P2	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260730H19-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,03	190,87	-	19/08/2026	H9	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)		ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,03	190,87	-	19/08/2026	H9	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)		ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	180,00	-	19/08/2026	H9	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)		ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	180,00	-	19/08/2026	H9	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)		ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,02	180,00	-	19/08/2026	H9	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)		ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,05	161,27	-	19/08/2026	H10	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H10-1	ER-1026 E.R. GAFA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Ask (generation)	123653 - TW202 (G)	0,05	161,27	-	19/08/2026	H10	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H10-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	161,27	-	19/08/2026	H10	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H10-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	161,27	-	19/08/2026	H10	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H10-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,02	161,27	-	19/08/2026	H10	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H10-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,05	87,57	-	19/08/2026	H11	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H11-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,05	87,57	-	19/08/2026	H11	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H11-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	87,57	-	19/08/2026	H11	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H11-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	87,57	-	19/08/2026	H11	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H11-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,02	87,57	-	19/08/2026	H11	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H11-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,05	18,64	-	19/08/2026	H12	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H12-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,03	18,64	-	19/08/2026	H12	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H12-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,02	18,64	-	19/08/2026	H12	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H12-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	18,64	-	19/08/2026	H12	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H12-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	18,64	-	19/08/2026	H12	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H12-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0	18,64	-	19/08/2026	H12	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H12-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,06	2,72	-	19/08/2026	H13	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H13-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,06	2,72	-	19/08/2026	H13	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H13-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,06	2,72	-	19/08/2026	H13	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H13-1	ER-1030 E.R. SANTA EULALIA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Bid (consumption)	133106 - TW104 (C)	0,03	2,72	-	19/08/2026	H13	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H13-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,03	2,72	-	19/08/2026	H13	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H13-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,07	3,43	-	19/08/2026	H14	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H14-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,07	3,43	-	19/08/2026	H14	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H14-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,07	3,43	-	19/08/2026	H14	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H14-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	3,43	-	19/08/2026	H14	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H14-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,03	3,43	-	19/08/2026	H14	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H14-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,06	3,43	-	19/08/2026	H15	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H15-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,06	3,43	-	19/08/2026	H15	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H15-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,06	3,43	-	19/08/2026	H15	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H15-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	3,43	-	19/08/2026	H15	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H15-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,03	3,43	-	19/08/2026	H15	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H15-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,05	2,20	-	19/08/2026	H16	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H16-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,05	2,20	-	19/08/2026	H16	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H16-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	2,20	-	19/08/2026	H16	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H16-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	2,20	-	19/08/2026	H16	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H16-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,02	2,20	-	19/08/2026	H16	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H16-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,05	4,04	-	19/08/2026	H17	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H17-1	ER-1026 E.R. GAFA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Ask (generation)	123653 - TW202 (G)	0,05	4,04	-	19/08/2026	H17	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H17-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,05	4,04	-	19/08/2026	H17	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H17-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	4,04	-	19/08/2026	H17	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H17-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,02	4,04	-	19/08/2026	H17	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H17-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,04	45,77	-	19/08/2026	H18	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H18-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,04	45,77	-	19/08/2026	H18	Wednesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H18-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,04	45,77	-	19/08/2026	H18	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H18-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,02	45,77	-	19/08/2026	H18	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H18-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,02	45,77	-	19/08/2026	H18	Wednesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H18-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,03	97,19	-	19/08/2026	H19	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H19-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,03	97,19	-	19/08/2026	H19	Wednesday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260819H19-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,01	97,19	-	19/08/2026	H19	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H19-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	97,19	-	19/08/2026	H19	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H19-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,02	97,19	-	19/08/2026	H19	Wednesday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260819H19-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,07	192,59	-	21/08/2026	H9	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H9-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,07	192,59	-	21/08/2026	H9	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H9-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,07	192,59	-	21/08/2026	H9	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H9-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	192,59	-	21/08/2026	H9	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H9-1	ER-1027 E.R. XENA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Bid (consumption)	96460 - TW105 (C)	0,03	192,59	-	21/08/2026	H9	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H9-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,07	106,96	-	21/08/2026	H10	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H10-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,07	106,96	-	21/08/2026	H10	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H10-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,07	106,96	-	21/08/2026	H10	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H10-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	106,96	-	21/08/2026	H10	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H10-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,03	106,96	-	21/08/2026	H10	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H10-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,08	41,70	-	21/08/2026	H11	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H11-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,08	41,70	-	21/08/2026	H11	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H11-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,08	41,70	-	21/08/2026	H11	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H11-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	41,70	-	21/08/2026	H11	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H11-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,04	41,70	-	21/08/2026	H11	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H11-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,09	2,92	-	21/08/2026	H12	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H12-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,09	2,92	-	21/08/2026	H12	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H12-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,09	2,92	-	21/08/2026	H12	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H12-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,05	2,92	-	21/08/2026	H12	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H12-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,04	2,92	-	21/08/2026	H12	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H12-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,09	2,05	-	21/08/2026	H13	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H13-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,09	2,05	-	21/08/2026	H13	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H13-1	ER-1026 E.R. GAFA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Bid (consumption)	115615 - TW101 (C)	0,09	2,05	-	21/08/2026	H13	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H13-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,05	2,05	-	21/08/2026	H13	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H13-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,04	2,05	-	21/08/2026	H13	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H13-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,09	2,00	-	21/08/2026	H14	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H14-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,09	2,00	-	21/08/2026	H14	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H14-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,09	2,00	-	21/08/2026	H14	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H14-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,05	2,00	-	21/08/2026	H14	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H14-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,04	2,00	-	21/08/2026	H14	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H14-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,08	2,00	-	21/08/2026	H15	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H15-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,08	2,00	-	21/08/2026	H15	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H15-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,08	2,00	-	21/08/2026	H15	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H15-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	2,00	-	21/08/2026	H15	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H15-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,04	2,00	-	21/08/2026	H15	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H15-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,08	2,00	-	21/08/2026	H16	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H16-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,08	2,00	-	21/08/2026	H16	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H16-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,08	2,00	-	21/08/2026	H16	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H16-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	2,00	-	21/08/2026	H16	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H16-1	ER-1027 E.R. XENA
Bid (consumption)	115615 - TW101 (C)	0,04	2,00	-	21/08/2026	H16	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H16-1	ER-1030 E.R. SANTA EULALIA

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Ask (generation)	110295 - TW201 (G)	0,07	2,74	-	21/08/2026	H17	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H17-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,07	2,74	-	21/08/2026	H17	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H17-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,07	2,74	-	21/08/2026	H17	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H17-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	2,74	-	21/08/2026	H17	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H17-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,03	2,74	-	21/08/2026	H17	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H17-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,07	16,00	-	21/08/2026	H18	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H18-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,07	16,00	-	21/08/2026	H18	Friday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H18-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,07	16,00	-	21/08/2026	H18	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H18-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,04	16,00	-	21/08/2026	H18	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H18-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,03	16,00	-	21/08/2026	H18	Friday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H18-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,06	80,24	-	21/08/2026	H19	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H19-1	ER-1026 E.R. GAFA
Ask (generation)	123653 - TW202 (G)	0,06	80,24	-	21/08/2026	H19	Friday	P3	Santa Eulàlia de Ronçana	AGE79 (generation)	20260821H19-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,06	80,24	-	21/08/2026	H19	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H19-1	ER-1030 E.R. SANTA EULALIA
Bid (consumption)	133106 - TW104 (C)	0,03	80,24	-	21/08/2026	H19	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H19-1	ER-1027 E.R. XENA
Bid (consumption)	96460 - TW105 (C)	0,03	80,24	-	21/08/2026	H19	Friday	P3	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260821H19-1	ER-1030 E.R. SANTA EULALIA
Ask (generation)	110295 - TW201 (G)	0,03	40,61	-	02/09/2026	H17	Tuesday	P4	Santa Eulàlia de Ronçana	AGE79 (generation)	20260901H17-1	ER-1026 E.R. GAFA
Bid (consumption)	115615 - TW101 (C)	0,03	40,61	-	02/09/2026	H17	Tuesday	P4	Santa Eulàlia de Ronçana	AGE78 (consumption)	20260901H17-1	ER-1030 E.R. SANTA EULALIA

Qualitative assessment of the results
Bringing UC Ib14 into the market largely depends on the final implementation of the mechanism of Local Flexibility Markets and the regulation of Flexible Connection Agreements as a legal figure in the national framework, which has been lately regulated for the first time [12]. Flexible Connection Agreements (FCAs) are now granted to Spanish electricity consumers only when firm grid capacity is unavailable at the requested node. Under these agreements, full electricity supply is not guaranteed for every hour of the year, requiring facilities to accept temporary power reductions or remote disconnections to maintain network security and manage congestion. To receive a grant, studies must demonstrate a minimum expected consumption window, which is set at least 62.5% of hours per year for pattern-based Type 0 permits and at least 90% for Type 1 and Type 2 permits. While all demand access requests from electricity storage facilities are automatically analysed as flexible access, several consumer types are strictly excluded from obtaining flexible connections, including essential services, collective urban or industrial projects legally obliged to respect electrification degrees, and installations required to have complementary safety power supplies. Depending on the connection network (distribution or transmission), voltage, and capacity, the regulations establish four distinct flexible access modalities (Types 0 to 3). These require specific grid-interactive technologies, ranging from local Smart Power Management Systems (SIGPF) and remote disconnection systems to mandatory participation in the system operator's Automatic Power Reduction System (SRAP) for large Type 3 transmission-connected consumers. Flexible Connection Agreements (FCAs) can play a pivotal role in improving the operational efficiency, competitiveness, and sustainability of local industrial sectors connected to distribution networks. Traditionally, industrial customers have been constrained by fixed connection capacities per contractual period. FCAs introduce a more dynamic intelligent layer by allowing industrial participants to temporarily exceed their firm connection limits when network conditions permit, creating a more efficient utilization of existing grid infrastructure and unlocking new opportunities for both energy consumers and producers. On the demand side, local industries increasingly face operational situations that require access to additional electrical capacity for limited periods. These may include unexpected production peaks driven by urgent production orders, the commissioning of additional manufacturing lines, the startup of large motors, furnaces, compressors or other energy-intensive equipment, and the rapid charging of electric vehicle fleets. Furthermore, industries with flexible processes or assets can increase consumption during periods of abundant local renewable generation or low energy prices by charging batteries, pre-heating processes, storing thermal energy, or advancing production schedules, improving both economic efficiency and system flexibility. On the generation side, FCAs provide distributed energy resources with opportunities to maximize the value of their assets. Industrial facilities equipped with photovoltaic systems or battery storage systems often encounter situations where generation exceeds their contracted export capacity. Without flexibility arrangements, this surplus energy may need to be curtailed, resulting in lost economic and environmental value. Through FCAs, these industrial generators can temporarily increase their export limits and deliver additional energy to neighbouring consumers or to the wider network whenever spare network capacity exists. This capability becomes particularly valuable during weekends, maintenance shutdowns, or periods of high renewable production when onsite consumption is low. FCAs also enable industrial battery systems to discharge energy during high-price periods and improve the business case for investments in distributed generation and storage technologies. In this context, the Distribution System Operator (DSO) evolves from its traditional role as a passive network operator into an active enabler of local industrial development and energy transition.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Rather than relying exclusively on expensive and lengthy network reinforcements, the DSO can facilitate the efficient use of existing assets through FCAs and flexibility markets. By enabling transaction according to network conditions.

With the regulated figures of LFM and FCAs, DSOs should have a favourable economic framework to implement the services with the enablement of the DT, allowing users connected to their grid to operate in local P2P markets without disrupting the service.

This scenario would imply the automation of some of the communication schemes established manually in TwinEU, such as the communication of matched offers between the LFM's LTS and the DSO's DT as well as the feedback on if a transaction can be accepted or must be disabled.

TwinEU has already established the communication and data exchange channels. This means that the actual implementation of the communication streams would only need a transposition of the proposed requirements into the regulatory framework for LFM and FCAs.

Table 28. Key Performance Indicator 1 for UC Ib14

KPI ID	Ib14-KPI1
KPI Name	Number of LFM sessions opened
Related Use Case	UC Ib14
KPI Description	Since the demonstration activities started, the number of market sessions where active offers were present. These offers were used to validate the functionality with the DT of the DSO's grid.
KPI Formula	$N = \sum_{i=1}^n A_i$
Variables explanation	N = the number of periods with active offers. n the number of intervals considered since the demonstration activities started. A _i the activity indicator for the period i.
Unit of measurement	Number of periods with active offers
Baseline	n.a.
KPI Value	34
Reference signal(s)	n.a.
Comments	n.a.

Table 29. Key Performance Indicator 1 for UC Ib14

KPI ID	Ib14-KPI2
KPI Name	Increased bidirectional (RES and loads) power hosting capacity
Related Use Case	UC Ib14
KPI Description	Total amount of energy that the UC definition and execution has allowed to be traded beyond the fixed contractual power limits of all participants.
KPI Formula	$E_{tot} = \sum_{i=1}^N E_i$
Variables explanation	E_{tot} = total traded energy. N the number of periods with active offers. E_i energy traded in session i.
Unit of measurement	MWh
Baseline	n.a.
KPI Value	3.51 MWh
Reference signal(s)	n.a.
Comments	n.a.

4 Conclusions

4.1 Summary of Achieved Results

This deliverable demonstrates that the TwinEU Digital Twin framework is already providing concrete and measurable value for both transmission and distribution system operation and planning. Across the three pilot environments (REE, Cuerva and ANELL) the project has advanced from conceptual design to the implementation and initial validation of digital-twin-enabled services addressing critical system needs such as contingency analysis, hosting capacity assessment, maintenance planning, renewable integration and flexibility-based operation.

For REE, the work carried out confirms the potential of AI-supported operational tools and synthetic climate data generation to improve control centre support and planning studies. The AI Agent for remedial action identification showed the ability to detect and mitigate voltage violations in a transmission-grid test case with fast response times, while the synthetic series generator demonstrated the capacity to provide historical, future and target-oriented meteorological datasets with low deviation from requested targets. These results represent a relevant step towards first, evaluate implementation of AI-based tools to support decision under complex operational scenarios and, second, to incorporate more robust long-term planning of the transmission system taking into account increased weather variability and uncertainty.

For the distribution-grid demonstrators, the achieved results also confirm the practical applicability of digital twins as decision-support and planning tools. In Cuerva's case, the document has defined a robust methodological basis for flexibility-oriented use cases focused on congestion mitigation and EV integration, establishing the analytical framework needed to exploit flexibility as an alternative to conventional reinforcement. In ANELL's case, the initial demonstrations have already produced operational evidence: the N-1 contingency assessment confirmed resilient grid behaviour under the analysed historical period, hosting-capacity calculations quantified the available bidirectional integration margins for generation and demand, and maintenance-planning simulations showed that Digital Twin forecasts and scenario-based security analyses can support outage preparation and real-time follow-up. Taken together, these developments confirm that the TwinEU approach is capable of linking data, simulation, forecasting and operational intelligence into a coherent support layer for modern grid management

4.2 Limitations and Lessons Learned

Despite the significant progress achieved, the work presented in this deliverable also highlights several limitations that are intrinsic to the current development stage of the demonstrators. In many cases, the use cases are still evolving from prototype or offline validation environments towards full operational deployment. This means that some functionalities have been validated only under selected scenarios, using historical datasets, simulated conditions, or limited real-world demonstrations. As a result, although the obtained results are promising, they should still be interpreted as an intermediate step rather than as a final operational benchmark.

One important lesson learned is the critical role of data quality, availability and interoperability. Across all demonstrators, the performance of the Digital Twin services depends heavily on the consistency of network topology models, SCADA and metering streams, historical records, and forecast inputs. Where these inputs are incomplete, heterogeneous or only partially observable, the resulting simulations and recommendations become more difficult to validate and operationalize. This has been

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

particularly visible in applications requiring real-time state estimation, maintenance-planning support or advanced hosting-capacity calculations, where the integration of multiple data sources is essential to maintain reliable and actionable outputs. One of such limitations, the spatial resolution of weather data is explored in Annex A.

Another relevant lesson concerns the balance between methodological sophistication and operational usability. Advanced AI, optimization, clustering and scenario-generation methods clearly expand the analytical power of the Digital Twin, but they also introduce requirements in terms of computational effort, explainability, configuration and user interaction. In addition, some use cases still require broader real-world validation over longer time periods and under a wider variety of operating conditions, including stressed scenarios and coordinated multi-actor interactions. Therefore, a key limitation at this stage is that not all developed functionalities have yet completed the transition from technically validated tools to fully integrated operational services.

4.3 Recommendations for Future Work

Future work should focus on consolidating the transition from isolated demonstrator functionalities to integrated and scalable Digital Twin services embedded in real operational environments. A first priority is to extend validation activities using a broader range of real data, more representative operating scenarios, and longer observation periods. This is particularly relevant for use cases involving AI-based control centre support, flexibility activation, maintenance planning and federated interaction between Digital Twins, where robustness under diverse system conditions must be demonstrated before wider deployment.

A second priority is to improve interoperability, automation and federation capabilities across the different Digital Twin layers and actors involved in the electricity system. This includes strengthening data exchange mechanisms, improving synchronization between operational and planning tools, and advancing interactions between DSO, TSO and market-oriented Digital Twins. In parallel, future developments should continue to enhance user-oriented aspects such as transparency of recommendations, visualization of results, ease of scenario configuration and explainability of AI outputs, so that system operators can trust and effectively use the provided services.

Finally, future work should deepen the assessment of the economic and systemic impact of the proposed solutions. Beyond technical feasibility, the project should quantify to what extent Digital Twin-enabled operation can reduce congestion costs, defer reinforcement investments, increase hosting capacity, improve maintenance efficiency and enhance resilience under growing renewable penetration and electrification. By coupling technical validation with business and operational impact assessment, TwinEU will be better positioned to demonstrate the replicability and long-term value of Digital Twin technologies for European power systems.

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Annex A Downscaling Techniques for Meteorological data

A.1 Introduction

Power system planning and renewable energy resource assessment increasingly rely on gridded meteorological datasets (reanalyses such as ERA5, regional climate projections from CORDEX and CMIP6, and operational ECMWF forecasts) as inputs to network planning, solar and wind resource characterisation, and adequacy studies. These datasets are typically distributed at spatial resolutions of 9-31 km, which is insufficient to represent the grid-relevant weather conditions at the scale of individual assets and feeders. Spatial downscaling, the generation of higher-resolution fields from coarser inputs, is therefore a prerequisite for credible high-resolution weather datasets supporting electricity network planning.

This section reviews the state of the art in spatial downscaling of near-surface wind speed, wind direction, direct horizontal irradiance and temperature, compares the main methodological families from a power-system perspective, and proposes an evidence-based direction for future dataset development. The review is based exclusively on published literature and methodological considerations. Wind speed and wind direction receive particular attention, since these variables are most strongly affected by terrain, surface roughness, coastal transitions and complex topography, and are simultaneously the most consequential for wind resource assessment and grid balancing.

A.2 Downscaling approaches

Four methodological families dominate the literature on spatial downscaling relevant to energy applications: dynamical downscaling, statistical downscaling, machine-learning downscaling, and hybrid approaches that combine elements of the above. A fifth, narrower category of physically constrained microscale flow models is treated separately because of its specific relevance to wind resource assessment.

A.2.1 Dynamic Downscaling

Dynamical downscaling nests a limited-area numerical prediction model (NWP) or regional climate model (RCM) within boundary conditions supplied by a coarser reanalysis or global climate model, and integrates the full set of atmospheric equations at higher resolution [7] [22]. The EURO-CORDEX initiative exemplifies this approach at continental scale, coordinating RCM simulations at 12.5 km and, in higher-resolution configurations, down to a few kilometres over Europe [23]. For wind energy specifically, the New European Wind Atlas (NEWA) applied WRF at approximately 3 km horizontal resolution across Europe, followed by microscale refinement and demonstrated that the WRF step alone reduced the mean wind-speed bias relative to the driving ERA5 reanalysis from about -1.5 ± 1.3 m/s to 0.02 ± 0.78 m/s when evaluated against tall-mast observations [24].

Dynamical downscaling explicitly resolves orographic flow detection, thermally driven local circulations, land-sea contrasts and boundary-layer processes, which makes it well suited to wind direction, a variable governed by these same physical mechanisms. It also produces mutually consistent multi-variable output (wind, temperature, radiation, humidity) and extends more reliably to unobserved regions and to future climate scenarios than data-driven methods, because it does not depend on local training data. Its principal weakness are extremely high computational cost, sensitivity to model physics parametrisation choices (planetary boundary layer and land-surface schemes in

particular), and non-trivial calibration burden, which typically limit its application to at most a few reference years or scenario slices rather than long continuous multi-decal series [22].

Table 30. Suitability of dynamical downscaling for each renewable energy-relevant meteorological variable.

VARIABLE	SUITABILITY
Wind speed	High
Wind direction	High
Irradiance	Medium (Cloud microphysics remains a source of error)
Temperature	High

A.2.2 Statistical Downscaling

Statistical downscaling establishes an empirical transfer function between coarse-resolution predictors and local-scale predictands, calibrated against historical observations or a reference high-resolution dataset. Techniques range from linear and multiple regression, quantile mapping and analogue methods, to more elaborate approaches incorporating topographic covariates [25]. In the wind energy domains, statistical regression-based downscaling that integrates topographic descriptors with meteorological descriptors has been reported to reduce predictive error relative to simpler baseline models [26]. A closely related and operationally mature variant is the numerical-wind-atlas / microscale-modelling method implemented in WAsP, which downscales a generalised wind climate using linearised flow physics and high-resolution terrain and roughness maps. This approach underlines the Global Wind Atlas and has been shown to correct systematic underestimation of wind resource in complex terrain, which can reach 100% when resource is evaluated directly from coarse reanalysis [27].

Table 31. Suitability of statistical downscaling for each renewable energy-relevant meteorological variable.

VARIABLE	SUITABILITY
Wind speed	Medium-High where terrain-aware formulations (for example WAsP-type microscale models) are used, otherwise medium
Wind direction	Medium (linear flow models capture orographic turning reasonably well but struggle with highly complex or thermally driven flows)
Irradiance	Medium
Temperature	Medium-High

Statistical methods are computationally inexpensive, easy to implement and update, and can be tailored to specific sites or networks of sites. Their principal limitation is a strong dependence on the quality and density of the observational or reference dataset used for calibration. Comparative studies consistently report that no single statistical technique perform best across all regions and variables,

and transferability to areas without calibration data is limited [26]. Statistical downscaling also tends to underrepresent extremes and rare events, since transfer functions are fitted to the bulk of the historical distribution unless extremes are explicitly targeted [25].

A.2.3 Machine Learning Downscaling

ML downscaling reframes the coarse-to-fine mapping as a super-resolution problem borrowed from computer vision, using convolutional neural networks (CNNs), generative adversarial networks (GANs) or, more recently, diffusion models. DeepSD demonstrated single-image super resolution CNNs for climate variables. Höhle et al subsequently compared CNN architectures specifically for near-surface wind field downscaling and found that architectural choices materially affect the recovery of realistic fine-scale spatial structure at a fraction of the computational cost of dynamical downscaling [28] [29]. Generative approaches such as GANs and, increasingly, diffusion models are also used to produce stochastic ensembles that better represent small-scale variability and extremes than deterministic regression-based ML models [30].

The principal advantage of ML downscaling is inference speed once trained: a trained network can downscale large volumes of data (multi-decadal reanalyses, multi-model ensembles) in a fraction of the time required by dynamical simulation, making it attractive for producing long, continuous high-resolution datasets [31]. However, the literature consistently identifies geographic and temporal generalisation as the central limitation: models trained in data-rich regions typically require retraining, or exhibit substantial performance degradation, when applied to regions or periods not represented in the training data [32]. Because ML models are trained to reproduce the statistical relationship present in the training set, they can also under-represent physical processes and extremes that are rare or absent from that set, and they generally require large volumes of high-resolution reference data (precisely what is limited in the present project context).

Table 32. Suitability of machine learning downscaling for each renewable energy-relevant meteorological variable.

VARIABLE	SUITABILITY
Wind speed	Medium-High
Wind direction	Medium
Irradiance	Medium-High (well matched to cloud-driven spatial structure when adequate satellite training data exist)
Temperature	High

A.2.4 Hybrid Approaches

Hybrid approaches combine two of the above families to offset their individual weaknesses. The most established hybrid workflow in the wind-energy domain couples mesoscale dynamical downscaling (typically WRF) with microscale statistical/physical downscaling (typically WAsP), as implemented in the NEWA and Global Wind Atlas methodologies: the dynamical step resolves synoptic-to-mesoscale flow and thermally driven circulations, while the microscale step efficiently accounts for fine-scale orographic speed-up, roughness-driven wind turning and vertical profile changes at a computational cost far lower than extending the dynamical model to the same resolution [24] [27]. A second emerging hybrid direction couples dynamical reanalysis output with ML-based

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

residual correction or super-resolution, for example using a dynamical model to capture mountain-flow physics and a deep-learning correction step to refine local bias, or using ML emulators trained on dynamically downscaled data to extend coverage to additional years or scenarios at much lower cost [31] [33].

Hybrid methods generally achieve the best trade-off between physical realism and computational tractability reported in the literature and are increasingly used to generate operational renewable-energy datasets. Their main drawbacks are increased methodological complexity, the need to validate each stage of the chain separately, and residual dependence of the ML or statistical component on training data availability and quality.

Table 33. Suitability of Hybrid approaches to downscaling for each renewable energy-relevant meteorological variable.

VARIABLE	SUITABILITY
Wind speed	High
Wind direction	High, provided the physically resolving component (dynamical or microscale flow model) retains responsibility for the terrain-driven turning of the wind
Irradiance	Medium-High
Temperature	High

A.2.5 Emerging Approaches

Two developments are worth noting for future dataset generations. First, generative diffusion models are being applied directly to kilometre-scale atmospheric downscaling, with early results suggesting improved representation of fine-scale variability and better-calibrated uncertainty relative to deterministic CNN/GAN approaches (deterministic in the sense that a single solution is given), although evidence specific to power-system applications remains limited. Second, ML-based emulators are being used to downscale large multi-model CMIP6 ensembles for renewable-energy drought and system-adequacy studies, providing a computationally feasible route to propagate climate-model uncertainty to high resolution [33] [31].

A.3 Comparative Assessment of Downscaling Approaches

The table below summarizes the qualitative comparison of the four main approach families against the criteria specified for this review, ordered by priority. Ratings reflect the balance of evidence in the reviewed literature rather than any single study and should be read as indicative rather than any single study and should be read as indicative rather than quantitative.

Table 34. Comparison of downscaling techniques on renewable energy criteria.

Criterion	Dynamical	Statistical	Machine Learning	Hybrid	Priority
Accuracy (regional mean state)	High	Medium–High	Medium–High	High	Highest
Reliability across events/periods	Medium–High	Medium	Medium	High	Highest
Reproduction of extremes	High	Low–Medium	Medium	Medium–High	Highest
Suitability for RE resource modelling	High	Medium	Medium–High	High	Highest
Suitability for power-system studies	Medium–High	Medium	Medium	High	Highest
Data requirements (training/obs.)	Low (physics-based)	Medium–High	High	Medium–High	High
Transferability across regions	Medium–High	Low–Medium	Low (w/o retraining)	Medium	High
Scalability (domains, variables)	Low	Medium	High	Medium	Medium
Ease of implementation	Low	High	Medium	Low–Medium	Medium
Explainability	High	Medium–High	Low–Medium	Medium	Lower
Computational cost	Very High	Low	Medium (training); Low (inference)	High	Lower

A.3.1 Accuracy, reliability and extremes

For mean-state accuracy and reliability, dynamical and hybrid dynamical/microscale workflows show the most consistent positive evaluation in the literature, particularly for wind speed and direction in complex terrain: the NEWA evaluation against tall masts reported a clear reduction in bias and spread relative to the driving reanalysis after WRF downscaling, with a further, terrain-dependent

improvement from the WAsP microscale step [24]. Purely statistical and purely ML approaches show more variable performance across regions and studies, and the literature explicitly cautions that no single statistical downscaling method is optimal for all regions [22]. Regarding extremes, dynamical models (which resolve the governing physics) and generative ML approaches such as those using GAN/Diffusion (which represent stochastic small-scale variability rather than a single deterministic best estimate) are reported to better preserve extreme values than deterministic regression-based statistical or CNN methods, which tend to smooth the tails of the distribution [25] [30].

A.3.2 Renewable-energy and power-system suitability

For wind resource assessment specifically, the literature repeatedly documents that coarse reanalysis alone systematically underestimates the exploitable resource, with underestimation of the windiest sites reaching up to 100% in complex terrain when small-scale spatial variability is not resolved [34] [35] [36]. This finding, replicated across successive versions of the Global Wind Atlas and multiple national wind atlases, is one of the most robust and repeatedly reported results in the field, and is a central justification for any downscaling effort in this project. For power-system studies more broadly, recent work highlights a persistent disconnect between the resolution and process representation of climate/weather datasets and the requirements of energy-system models and advocates closer integration between the two communities as datasets move to higher resolution [37]. Solar irradiance downscaling for power-system applications has followed a somewhat different, largely physics-based or satellite-statistical trajectory (rather than the dynamical/ML split dominant for wind), reflecting the strong dependence of irradiance on cloud fields that are better constrained by satellite observation than by NWP microphysics alone [38].

A.3.3 Data requirements and transferability

Data requirements and transferability are identified together in the table because they are closely linked in practice: methods with lower observational data requirements at the point of application (dynamical downscaling, and statistical/microscale methods built on physical flow models such as WAsP) tend to transfer more readily to regions without dense observation networks, since their skill derives from resolved or parameterised physics rather than from statistical fitting to local observations [23] [27]. Conversely, ML downscaling requires the largest volumes of high-resolution training data and shows the weakest transferability to regions or periods outside its training distribution: a recent benchmark constructed specifically to test this property found substantial performance degradation when models trained in data-rich regions were applied to data-scarce regions, even though performance within the training domain remained strong [32]. This is a directly relevant finding for the present project, given the explicitly limited access to dense observational networks.

A.3.4 Scalability, ease of implementation, explainability and cost

On the lower-priority criteria, the trade-offs are broadly inverse to those above. ML methods, once trained, scale efficiently to large data volumes and multiple variables at low marginal inference cost, and are comparatively straightforward to apply to new time periods within the same domain, but are the least explainable of the four families and carry a substantial upfront training cost and data-engineering burden [33]. Dynamical downscaling is the most explainable, in the sense that its behaviour can be traced to explicit physical parameterizations but is the least scalable and by far the most computationally expensive, particularly at 1-3 km resolution over large domains and long periods [22]. Statistical and microscale methods sit between these extremes, offering low computational cost and high ease of implementation once a suitable flow or regression model is set up, at the expense of some loss of physical generality outside their calibration conditions.

A.4 Recommended Approach for the DT

No single approach dominates across all criteria, and the evidence reviewed does not support selecting the most methodologically sophisticated option by default. The recommendation below follows directly from the comparative assessment and from the specific constraints stated for this project: limited access to dense observational data, a requirement for transferability across the project's area(s) of interest, a target resolution of 1-3 km, the priority placed on wind speed and wind direction, and the need for results that are practically applicable within power-system studies rather than primarily of academic interest.

A hybrid dynamical-plus-microscale workflow, following the methodology established by the New European Wind Atlas and the Global Wind Atlas, is recommended as the primary strategy for wind speed and wind direction. Mesoscale dynamical downscaling (WRF for example) to a few kilometres captures synoptic and mesoscale flow modification, thermally driven circulations and coastal transitions without requiring local training data, addressing the transferability constraint directly. The subsequent microscale step (WASP-type linearised flow modelling, for example) refines orographic speed-up, roughness-driven wind turning and vertical structure to 1-3 km or finer at comparatively low additional computational cost, and has demonstrated, repeatedly, a further reduction of bias relative to the mesoscale step alone [24] [27]. This combination directly targets the physical mechanisms (terrain, roughness, coastal effects) identified as the principal downscaling challenge for wind and does not depend on dense local observations for calibration, only for optional independent validation where available. The computational burden imposed by the mesoscale step is partially reduced by a concentrated wind farm fleet. Whilst the GCM's cover the whole energy system footprint, the downscaling method would only be applied to the cells with renewable energy assets.

Pure statistical downscaling is preferable mainly as a lower-cost fallback or for rapid, site-specific refinement where a reasonably dense reference dataset (a network of masts, or output from a prior dynamical run, for example) is already available, and where transferability beyond the calibration area is not required; given the stated limited observational access, it should be regarded as a secondary rather than primary strategy for the project's core wind fields, though it remains well suited to temperature, and reasonably suited to irradiance, downscaling given the weaker terrain-dependence of these variables. Pure ML downscaling is preferable where a large, high-resolution reference dataset already exists to train against (for instance, ML emulation of an existing dynamically downscaled wind atlas, or of dense satellite-derived irradiance products) and where the objective is to extend that reference cheaply to additional years, ensemble members or CMIP6 scenarios, rather than to generalize to a new, unobserved region. This emulator role (rather than stand-alone downscaling from reanalysis in data-scarce regions) is where ML currently offers the clearest evidence-based benefit for this project [31] [33]. Fully dynamical downscaling without a microscale step is preferable only where computational resources allow simulation close to the 1-3 km target resolution directly and where the added value of an additional microscale correction has not been demonstrated for the terrain in question. For most of the domain sizes and time periods relevant to grid-planning studies, running WRF-class models natively at 1-3 km over multi-decadal periods is unlikely to be practical within typical project budgets, reinforcing the case for the hybrid route.

For irradiance, a physically based or satellite-statistical downscaling approach, informed by cloud-resolving satellite products where available, is recommended in preference to dynamical downscaling alone, reflecting the literature finding that cloud microphysics remains a comparatively weak link in NWP-based irradiance estimation relative to satellite-constrained methods [38]. For temperature, all four families perform adequately. The choice should be driven by consistency with the wind and

irradiance workflow (i.e., temperature can be obtained as a by-product of whichever primary dynamical or hybrid chain is adopted for wind) rather than by temperature-specific considerations. Across all variables, an ML-based residual-correction or emulation layer applied on top of the dynamical/hybrid backbone is a reasonable and evidence-supported future development once an initial reference dynamical dataset exists for the project's domain, since this configuration benefits from ML's low inference cost and scalability while avoiding its principal weakness (poor transferability to un-trained regions) by only ever being asked to emulate a domain it has already seen [33] [39].

A.5 Conclusions

The literature on spatial downscaling of meteorological data for renewable-energy and power-system applications supports several consistent conclusions. Coarse-resolution reanalysis and climate products systematically misrepresent the local wind resource, particularly in complex terrain, and downscaling to the 1-3 km range is necessary rather than optional for credible grid-planning datasets [27] [35]. Dynamical downscaling offers the most physically grounded and transferable representation of wind speed and, critically, wind direction, but at high computational cost. Statistical and microscale methods are cheap and effective refinements of dynamical output but depend on physical flow assumptions or local data for their own skill. ML downscaling offers unmatched inference-time efficiency and scalability but is currently constrained by limited geographic and temporal generalisation, which is a material concern given this project's limited observational access [32].

The principal trade-off for the project is therefore between physical robustness and transferability on one hand (favouring dynamical and hybrid dynamical/microscale methods) and computational and data efficiency on the other (favouring statistical and ML methods). The evidence reviewed indicates that this trade-off is best resolved, for wind speed and wind direction, by a hybrid mesoscale-dynamical-plus-microscale workflow consistent with established wind-atlas methodology, complemented where appropriate by satellite-informed downscaling for irradiance and by ML-based emulation once a suitable dynamical reference dataset exists. The most promising direction for future high-resolution weather datasets supporting electricity network planning is not a single algorithm but a staged model chain (physically resolving methods establishing the reference climatology and its transferability, with statistical or ML components used selectively to reduce cost or extend coverage once that reference exists) together with continued attention, as recommended throughout the reviewed literature, to explicit quantification of downscaling uncertainty and to closer alignment between meteorological dataset design and the specific requirements of power-system models [37].

Annex B Further test cases for UC-Ib07

Table 35. Test case 2 for UC Ib07

Test Case ID	TC Ib07.2
Name	DT-based grid maintenance planning and N-1 assessment
Related UC	UC Ib07
Timeframe	15/05/2026 10:00h - 15/05/2026 12:30h
Targets	Validate the Digital Twin (ETER) for planning grid maintenance activities (e.g., line disconnection for concrete pole installation). Perform load and generation forecasts for the outage period and execute N-1 contingency analysis to ensure the grid remains resilient during the maintenance. Calculate the accuracy of the DT predictions compared to real-world data using MAPE.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider, with a functionality to simulate forecasts, optimal power flows and N-1 contingency analysis.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. Smart meter data (exported and imported power).
Triggering Event	Scheduled maintenance for substation CT-0259
Pre-condition	• Network topology loaded and validated in ÉTER. • Forecasting and N-1 Contingency services deployed and integrated within the DT. Real-time SCADA and concentrator data streams active.
Experiment description	1) Identify the substation CT-0259 to be disconnected over the maintenance timeframe 15/05/2026 10h to 15/05/2026 12:30h. 2) Generate forecasts in ETER for the maintenance window. 3) Run power-flow simulations for these forecast hours with the specific line out of service to identify potential issues. 4) Perform N-1 contingency analysis on the remaining network to ensure security of supply if another fault occurs during maintenance. 5) Save the forecasted power flow states. 6) Once maintenance occurs, gather real-time data. 7) Compare forecasted vs. real values.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Post-condition	Maintenance viability is validated. The grid is verified to be N-1 contingent during the outage. Forecast accuracy (MAPE) is calculated and stored.
Datasets required for the experiment	- MV network topology. - Forecasted load and generation profiles. Real-time SCADA and metering data recorded during the actual maintenance activity.
Field data to be gathered	- Forecasted power flow values (P, Q, V, I). - Real-time power flow values. - MAPE (Mean Absolute Percentage Error) of the deviation. List of operational violations (if any) during simulation.
Related KPIs	lb07-KPI1: Accuracy in recalculated power flows.

Results of the experiment

The experiment focused on a real maintenance operation: construction work on CT-0259, which required a scheduled outage from May 15th, 2026 (10:00) to May 15th, 2026 (12:30)

The ETER tool allowed for a detailed simulation of this disconnection:

- Forecast Generation:** Using the Forecast tab, a slider was used to select the specific hour to perform forecast, see Figure 48.

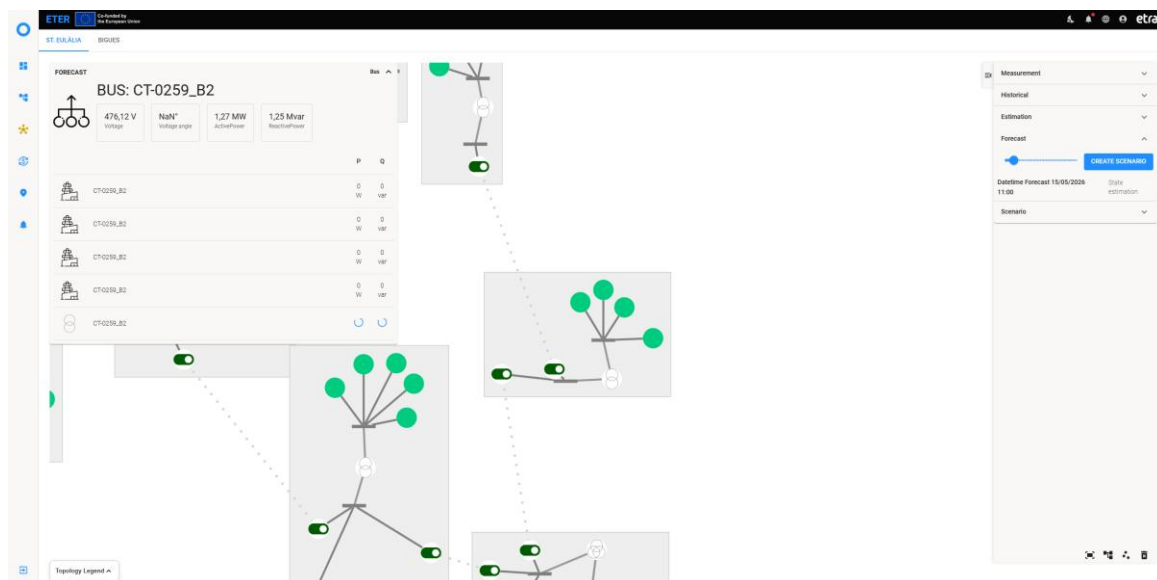


Figure 48. ETER GUI, forecast tab. CT-0259.

- Scenario Creation:** A specific scenario was created where the substation CT-0259 was disconnected by closing its respective switches in the Digital Twin interface, see Figure 49.

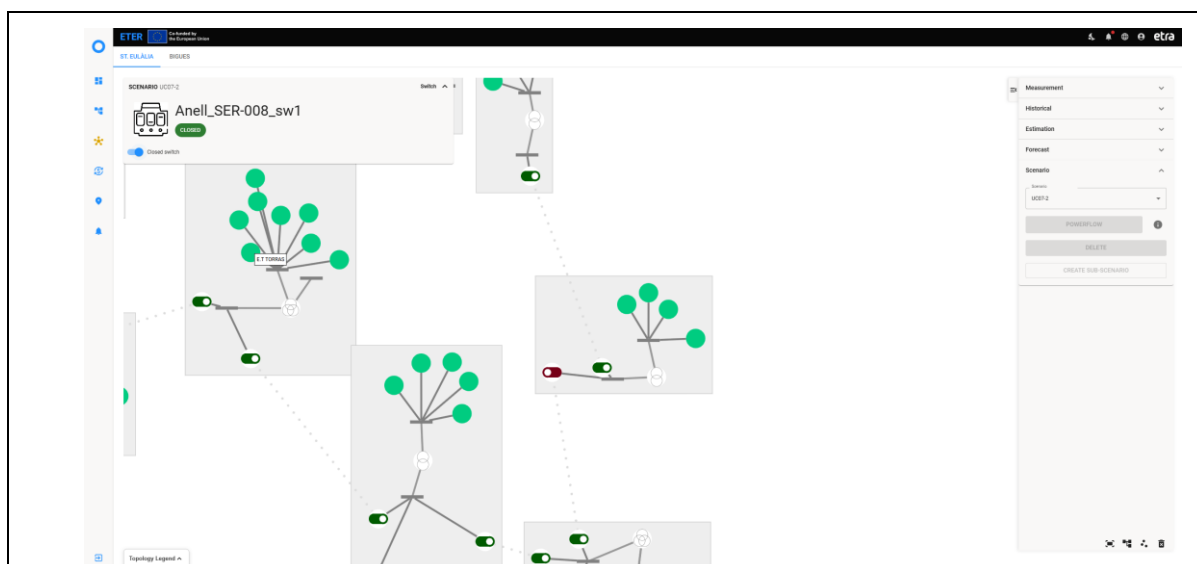


Figure 49. ETER GUI, scenario switch closure. CT-0259.

The scenario was then updated to analyse the resulting grid state and power flow redistribution, see Figure 50.

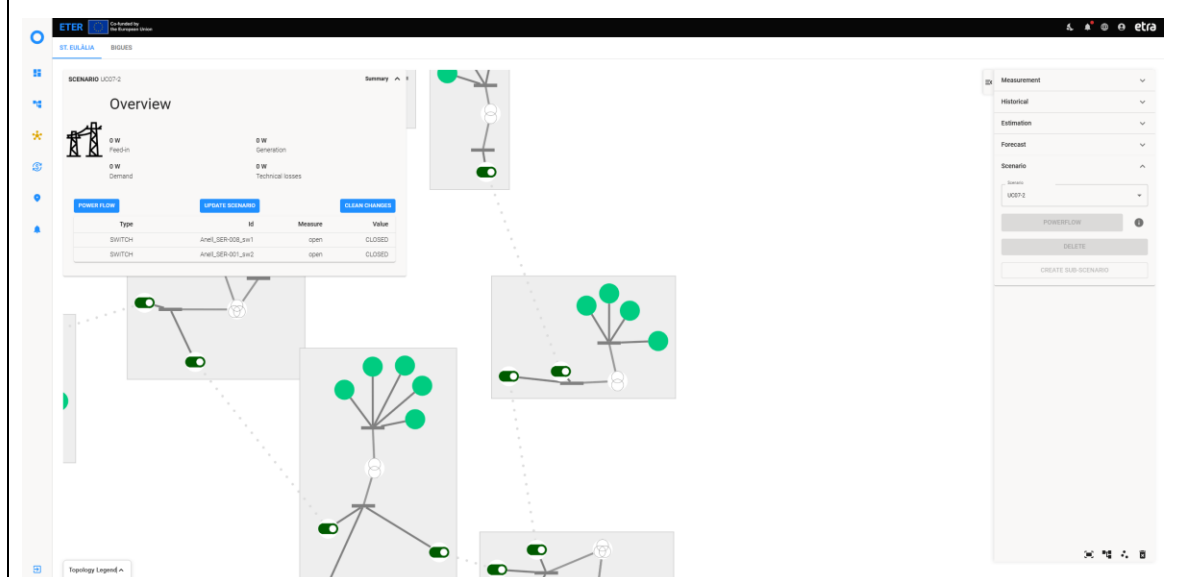


Figure 50. ETER GUI, scenario update with new changes. CT-0259.

- **N-1 Security Analysis:** This outage scenario was loaded into the N-1 Contingency Analysis module to verify that the grid remained resilient if a second line were to fail during the works, see Figure 51.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

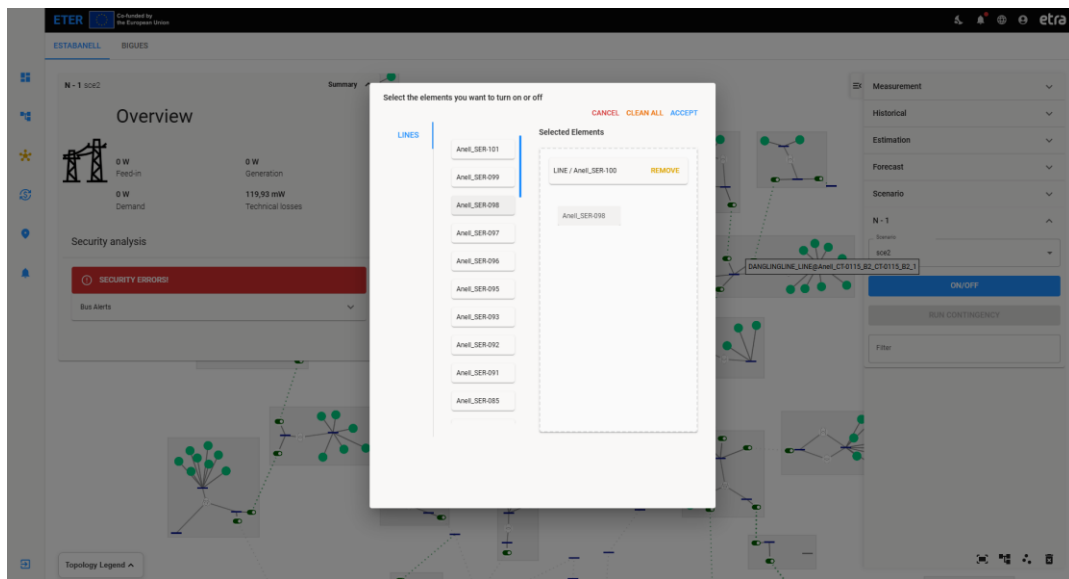


Figure 51. ETER GUI, N-1 Contingency Analysis module. CT-0259.

ETER generated sub-scenarios for every tested line to visualize the grid status after each potential second contingency, see Figure 52.

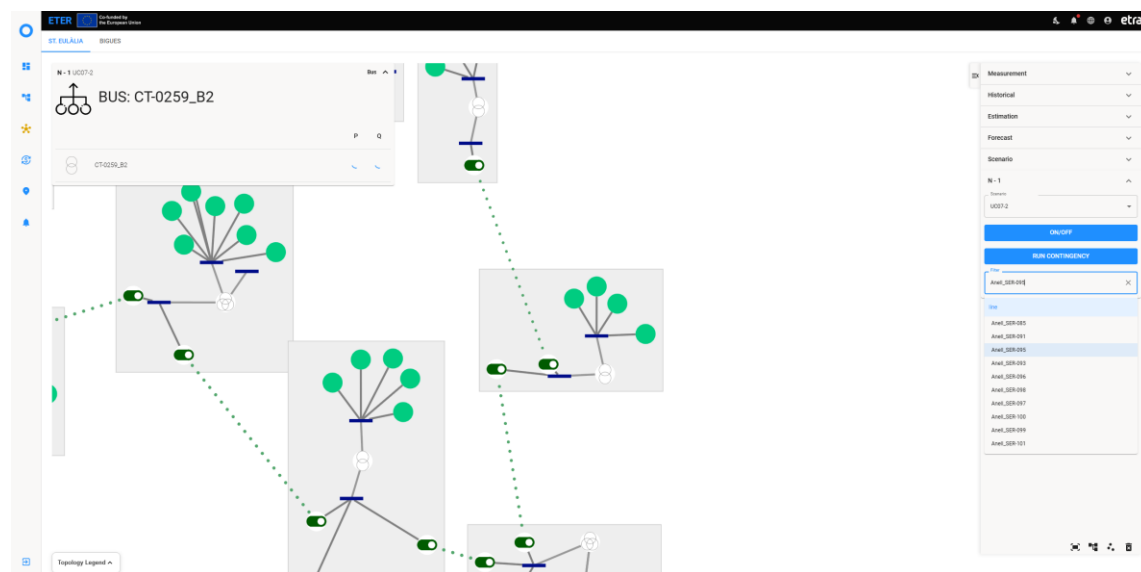


Figure 52. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0259.

An offline process executed the N-1 study for every hour of the forecast window for each substation, see Figure 53 and Figure 54 as examples, finding no operational violations or security issues for the planned maintenance.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

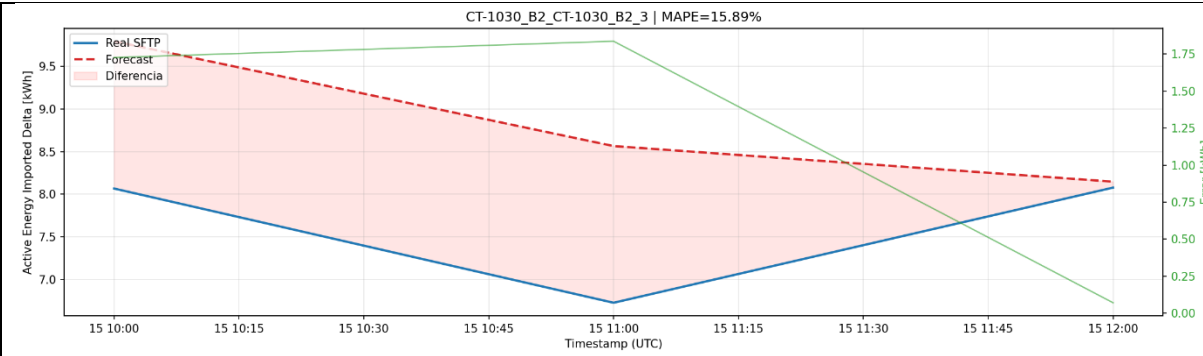


Figure 53. Forecast evolution of substation CT-1030 during maintenance.

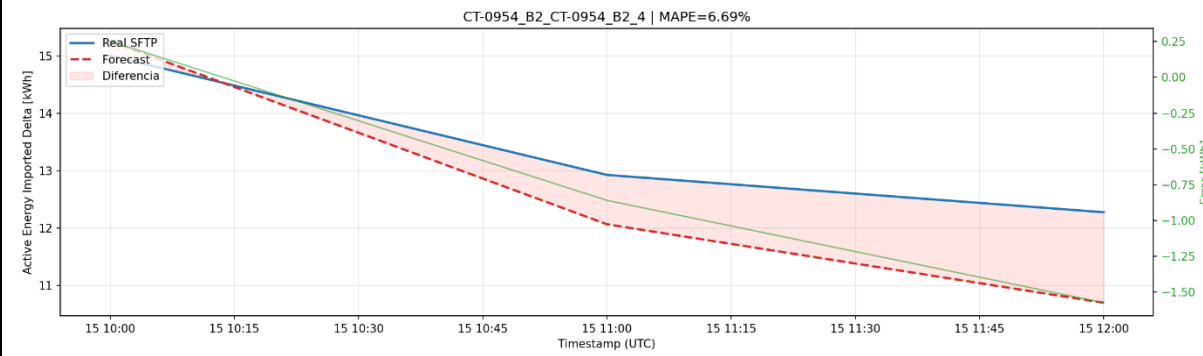


Figure 54. Forecast evolution of substation CT-0954 during maintenance.

During the actual work, a real-time process was used to monitor the grid. Because SCADA visibility is limited to specific substations, the system combined forecasts, SCADA data, and concentrator data to perform a continuous State Estimation and N-1 analysis, ensuring no power flow or stability problems occurred.

Finally, the real data from the concentrators was compared to the hourly predicted active power at each substation. As this is a regression problem, the accuracy was measured using MAPE (Mean Absolute Percentage Error), resulting in an average MAPE of 18.68% for the recalculated power flows considering 43 substations.

Qualitative assessment of the results

The test case successfully validated the ETER Digital Twin (DT) as a reliable tool for planning grid maintenance activities, specifically for substation CT-0259. The DT demonstrated its capacity to integrate load and generation forecasts, simulate power flow redistribution under outage conditions, and perform comprehensive N-1 contingency analysis to ensure grid resilience throughout the maintenance window.

The system successfully generated hourly forecasts for active power at 43 substations over the entire maintenance period, which were visualized through the ETER interface. This allowed operators to anticipate grid behaviour before the physical disconnection occurred and make informed decisions about the feasibility of the planned outage.

Scenario simulation was another key capability demonstrated during the test. By closing the switches associated with substation CT-0259 in the DT interface, a realistic outage scenario was created that accurately reflected the intended maintenance activity. The system automatically recalculated power flows and updated the grid state to reflect the new topology, confirming that no operational violations such as overloads or voltage violations would arise from the planned maintenance.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

The N-1 contingency analysis provided an additional layer of security validation for the maintenance planning process. The DT executed an offline N-1 study for every hour of the forecast window across all substations, systematically evaluating the impact of each credible single contingency. This analysis verified that even if an additional line/substation failed during the maintenance works, the grid would remain secure and stable, with no security issues detected throughout the entire maintenance period.

Prediction accuracy was evaluated by comparing forecasted versus real concentrator data collected during the actual maintenance activity. Using Mean Absolute Percentage Error (MAPE) as the metric for this regression problem, the average MAPE across 43 substations was 18.68%. This indicates a reasonably accurate predictive performance for planning purposes.

The test case confirmed that the ETER Digital Twin can create "what-if" scenarios that incorporate forecasted load and generation profiles, enabling proactive planning of maintenance activities with confidence. Operators can simulate switch operations to model line/substation disconnections and immediately observe the impact on power flows and grid stability, while the automated N-1 module evaluates all credible contingencies for each hour of the forecast window.

Table 36. Test case 3 for UC Ib07

Test Case ID	TC Ib07.3
Name	DT-based grid maintenance planning and N-1 assessment
Related UC	UC Ib07
Timeframe	10/06/2026 from 7:45h to 11:00h
Targets	Validate the Digital Twin (ETER) for planning grid maintenance activities (e.g., line disconnection for concrete pole installation). Perform load and generation forecasts for the outage period and execute N-1 contingency analysis to ensure the grid remains resilient during the maintenance. Calculate the accuracy of the DT predictions compared to real-world data using MAPE.
Actors involved	- ANELL - Grid Operator. It provides data (historical and real-time). - ETRA – ÉTER technology provider, with a functionality to simulate forecasts, optimal power flows and N-1 contingency analysis.
Assets and systems involved	- ETER - SCADA (P, Q, V, I) from the nodes. Smart meter data (exported and imported power).
Triggering Event	Scheduled maintenance for substation CT-0265
Pre-condition	- Network topology loaded and validated in ÉTER. - Forecasting and N-1 Contingency services deployed and integrated within the DT. Real-time SCADA and concentrator data streams active.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Experiment description	1) Identify the substation CT-0265 to be disconnected over the maintenance timeframe 10/06/2026 7:45h to 11:00h. 2) Generate forecasts in ETER for the maintenance window. 3) Run power-flow simulations for these forecast hours with the specific line out of service to identify potential issues. 4) Perform N-1 contingency analysis on the remaining network to ensure security of supply if another fault occurs during maintenance. 5) Save the forecasted power flow states. 6) Once maintenance occurs, gather real-time data. 7) Compare forecasted vs. real values.
Post-condition	Maintenance viability is validated. The grid is verified to be N-1 contingent during the outage. Forecast accuracy (MAPE) is calculated and stored.
Datasets required for the experiment	• MV network topology. • Forecasted load and generation profiles. Real-time SCADA and metering data recorded during the actual maintenance activity.
Field data to be gathered	• Forecasted power flow values (P, Q, V, I). • Real-time power flow values. • MAPE (Mean Absolute Percentage Error) of the deviation. List of operational violations (if any) during simulation.
Related KPIs	lb07-KPI1: Accuracy in recalculated power flows.
Results of the experiment	
The experiment focused on a real maintenance operation: construction work on CT-0265, which required a scheduled outage from June 16th, 2026 (07:45) to June 16th, 2026 (11:00) The ETER tool allowed for a detailed simulation of this disconnection: • Forecast Generation: Using the Forecast tab, a slider was used to select the specific hour to perform forecast, see Figure 55.	

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

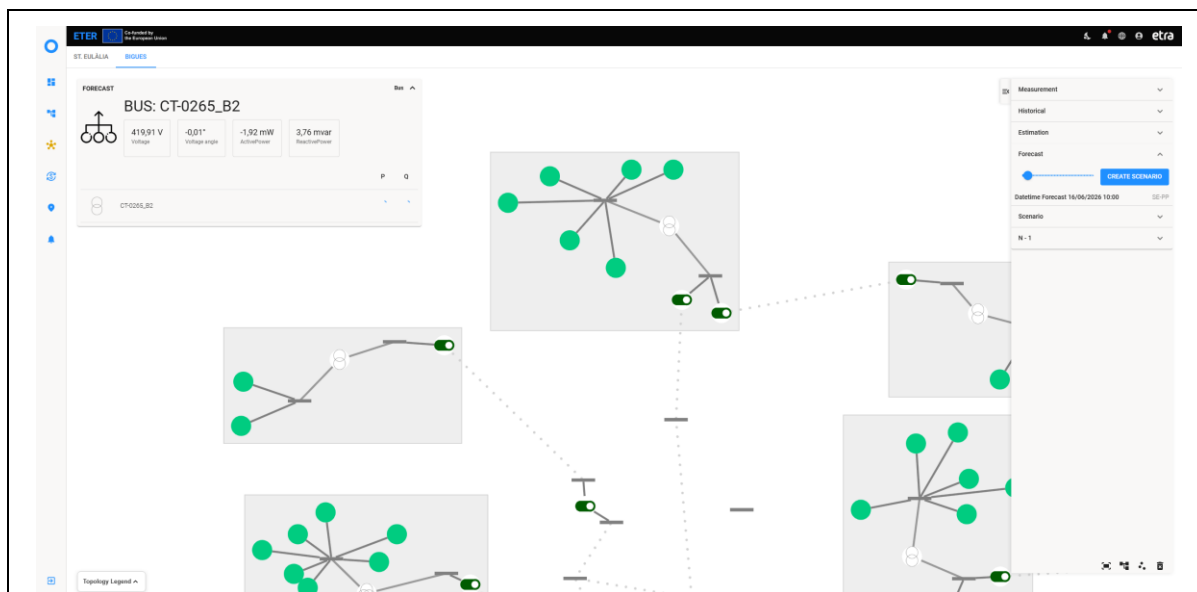


Figure 55. ETER GUI, forecast tab. CT-0265.

- **Scenario Creation:** A specific scenario was created where the substation CT-0265 was disconnected by closing its respective switches in the Digital Twin interface, see Figure 56.

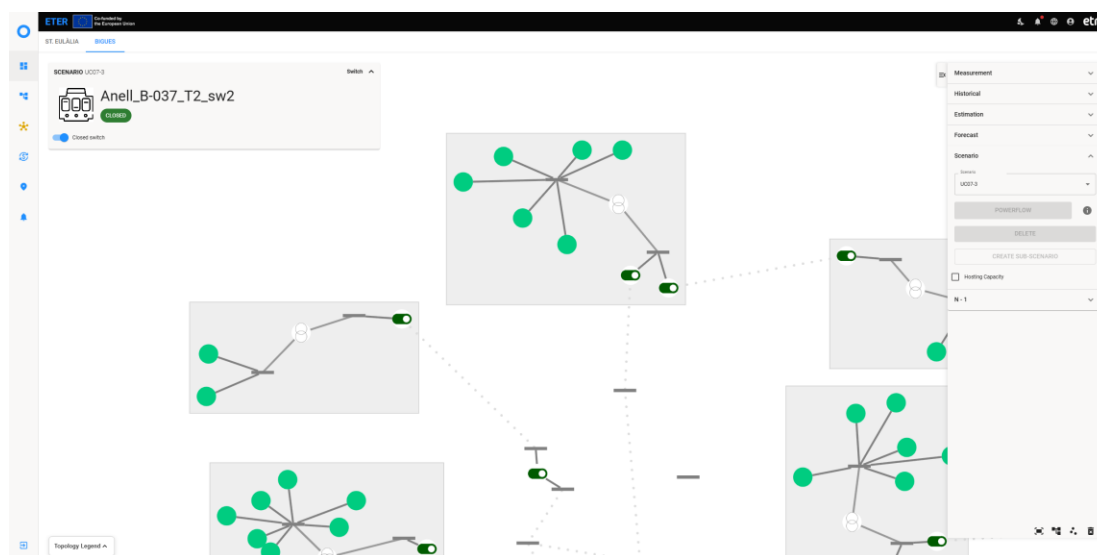


Figure 56. ETER GUI, scenario switch closure. CT-0265.

The scenario was then updated to analyse the resulting grid state and power flow redistribution, see Figure 57.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

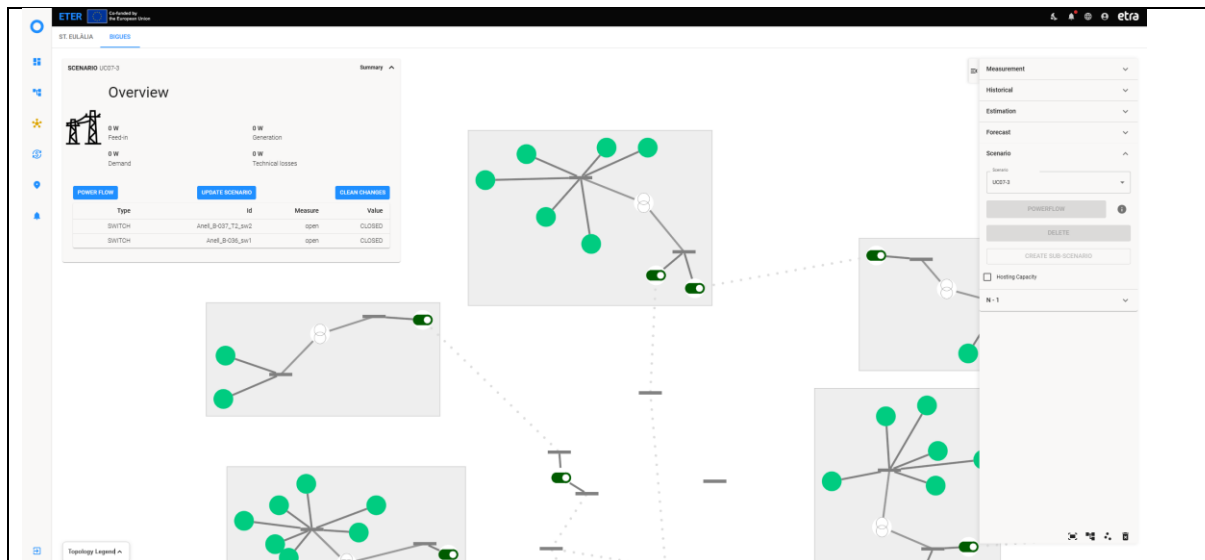


Figure 57. ETER GUI, scenario update with new changes. CT-0265.

- **N-1 Security Analysis:** This outage scenario was loaded into the N-1 Contingency Analysis module to verify that the grid remained resilient if a second line were to fail during the works, see Figure 58.

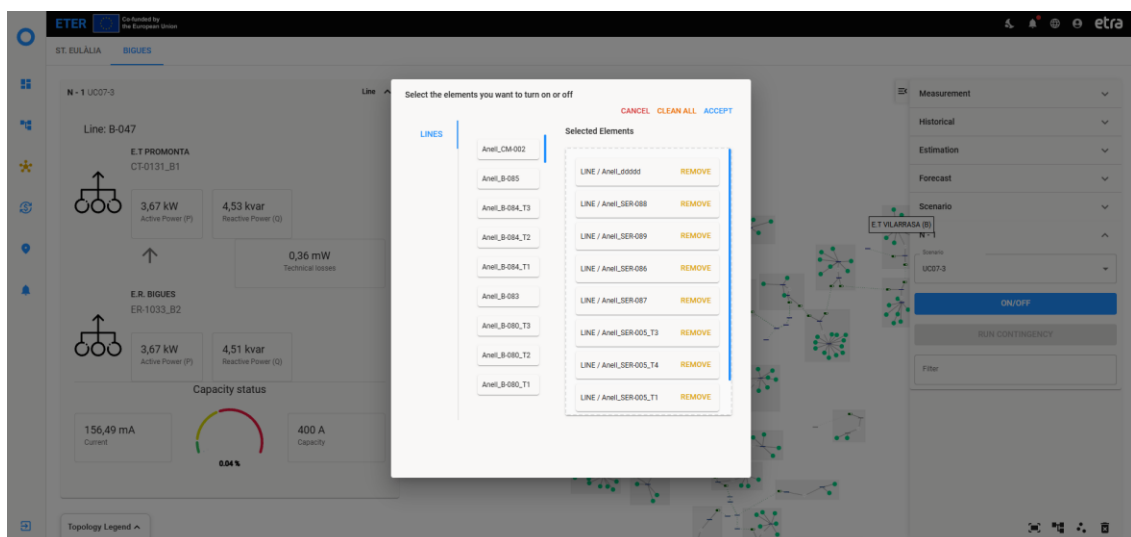


Figure 58. ETER GUI, N-1 Contingency Analysis module. CT-0265.

ETER generated sub-scenarios for every tested line to visualize the grid status after each potential second contingency, see Figure 52.

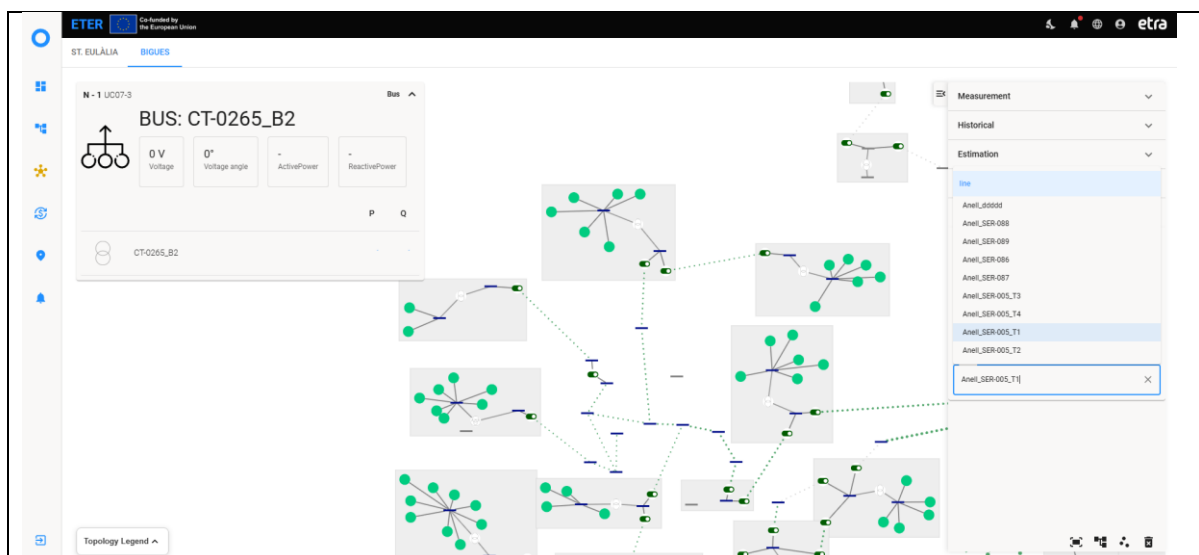


Figure 59. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0265.

An offline process executed the N-1 study for every hour of the forecast window for each substation, see Figure 60 and Figure 61 as examples, finding no operational violations or security issues for the planned maintenance.

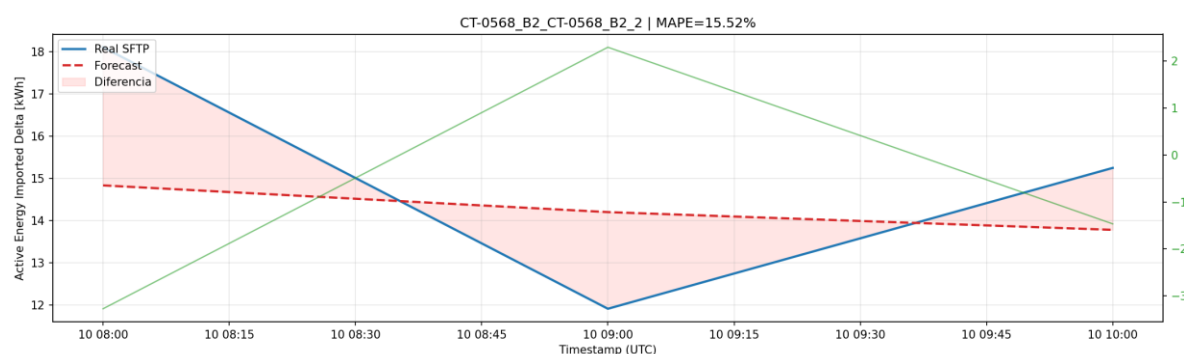


Figure 60. Forecast evolution of substation CT-0568 during maintenance.

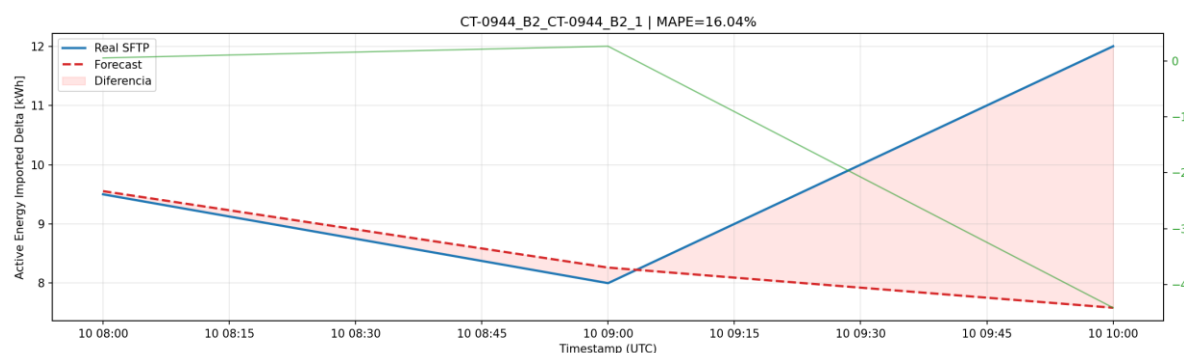


Figure 61. Forecast evolution of substation CT-0944 during maintenance.

During the actual work, a real-time process was used to monitor the grid. Because SCADA visibility is limited to specific substations, the system combined forecasts, SCADA data, and concentrator data to perform a continuous State Estimation and N-1 analysis, ensuring no power flow or stability problems occurred.

Finally, the real data from the concentrators was compared to the hourly predicted active power at each substation. As this is a regression problem, the accuracy was measured using MAPE (Mean

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Absolute Percentage Error), resulting in an average MAPE of 17.06% for the recalculated power flows considering 43 substations.

Qualitative assessment of the results

The test case successfully validated the ETER Digital Twin (DT) as a reliable tool for planning grid maintenance activities, specifically for substation CT-0265. The DT demonstrated its capacity to integrate load and generation forecasts, simulate power flow redistribution under outage conditions, and perform comprehensive N-1 contingency analysis to ensure grid resilience throughout the maintenance window.

The system successfully generated hourly forecasts for active power at 43 substations over the entire maintenance period, which were visualized through the ETER interface. This allowed operators to anticipate grid behaviour before the physical disconnection occurred and make informed decisions about the feasibility of the planned outage.

Scenario simulation was another key capability demonstrated during the test. By closing the switches associated with substation CT-0265 in the DT interface, a realistic outage scenario was created that accurately reflected the intended maintenance activity. The system automatically recalculated power flows and updated the grid state to reflect the new topology, confirming that no operational violations such as overloads or voltage violations would arise from the planned maintenance.

The N-1 contingency analysis provided an additional layer of security validation for the maintenance planning process. The DT executed an offline N-1 study for every hour of the forecast window across all substations, systematically evaluating the impact of each credible single contingency. This analysis verified that even if an additional line/substation failed during the maintenance works, the grid would remain secure and stable, with no security issues detected throughout the entire maintenance period.

Prediction accuracy was evaluated by comparing forecasted versus real concentrator data collected during the actual maintenance activity. Using Mean Absolute Percentage Error (MAPE) as the metric for this regression problem, the average MAPE across 43 substations was 17.06%. This indicates a reasonably accurate predictive performance for planning purposes.

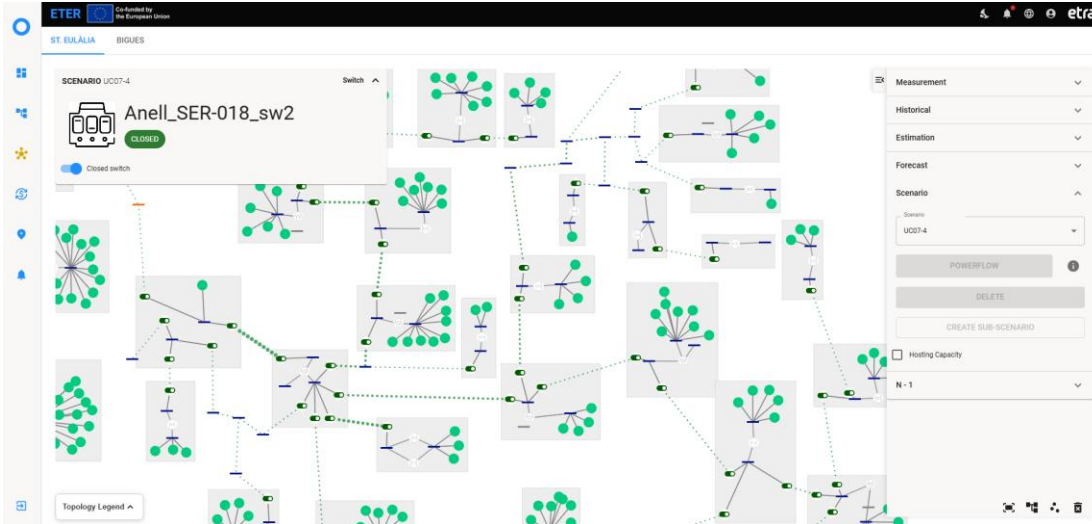
The test case confirmed that the ETER Digital Twin can create "what-if" scenarios that incorporate forecasted load and generation profiles, enabling proactive planning of maintenance activities with confidence. Operators can simulate switch operations to model line/substation disconnections and immediately observe the impact on power flows and grid stability, while the automated N-1 module evaluates all credible contingencies for each hour of the forecast window.

Table 37. Test case 4 for UC Ib07

Test Case ID	TC Ib07.4
Name	DT-based grid maintenance planning and N-1 assessment
Related UC	UC Ib07
Timeframe	14/06/2026 from 7:45h to 13:00h
Targets	Validate the Digital Twin (ETER) for planning grid maintenance activities (e.g., line disconnection for concrete pole installation). Perform load and generation forecasts for the outage period and

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

	execute N-1 contingency analysis to ensure the grid remains resilient during the maintenance. Calculate the accuracy of the DT predictions compared to real-world data using MAPE.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider, with a functionality to simulate forecasts, optimal power flows and N-1 contingency analysis.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. Smart meter data (exported and imported power).
Triggering Event	Scheduled maintenance for substation CT-0620
Pre-condition	• Network topology loaded and validated in ÉTER. • Forecasting and N-1 Contingency services deployed and integrated within the DT. Real-time SCADA and concentrator data streams active.
Experiment description	1) Identify the substation CT-0620 to be disconnected over the maintenance timeframe 14/06/2026 7:45h to 13:00h. 2) Generate forecasts in ETER for the maintenance window. 3) Run power-flow simulations for these forecast hours with the specific line out of service to identify potential issues. 4) Perform N-1 contingency analysis on the remaining network to ensure security of supply if another fault occurs during maintenance. 5) Save the forecasted power flow states. 6) Once maintenance occurs, gather real-time data. 7) Compare forecasted vs. real values.
Post-condition	Maintenance viability is validated. The grid is verified to be N-1 contingent during the outage. Forecast accuracy (MAPE) is calculated and stored.
Datasets required for the experiment	• MV network topology. • Forecasted load and generation profiles. Real-time SCADA and metering data recorded during the actual maintenance activity.
Field data to be gathered	• Forecasted power flow values (P, Q, V, I). • Real-time power flow values. • MAPE (Mean Absolute Percentage Error) of the deviation. List of operational violations (if any) during simulation.

Related KPIs	Ib07-KPI1: Accuracy in recalculated power flows.
Results of the experiment	
The experiment focused on a real maintenance operation: construction work on CT-0620, which required a scheduled outage from June 14th, 2026 (07:45) to June 14th, 2026 (13:00) The ETER tool allowed for a detailed simulation of this disconnection: Forecast Generation: Using the Forecast tab, a slider was used to select the specific hour to perform forecast, see Figure 62.	
	
Figure 62. ETER GUI, forecast tab. CT-0620. Scenario Creation: A specific scenario was created where the substation CT-0265 was disconnected by closing its respective switches in the Digital Twin interface, see Figure 63.	
	
Figure 63. ETER GUI, scenario switch closure. CT-0265. The scenario was then updated to analyse the resulting grid state and power flow redistribution, see Figure 64.	

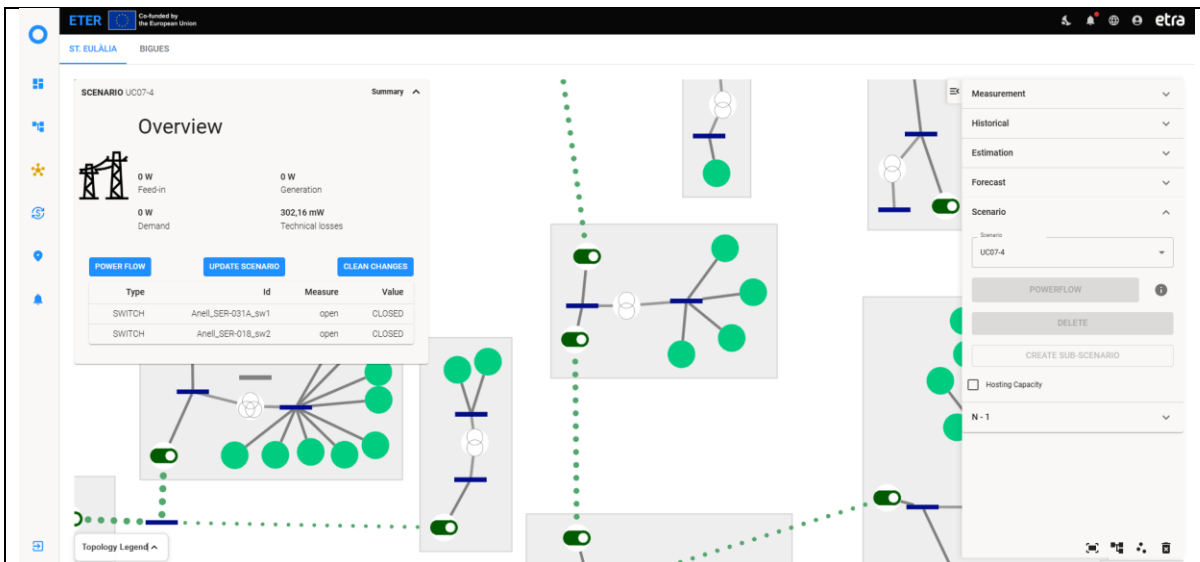


Figure 64. ETER GUI, scenario update with new changes. CT-0265.

- **N-1 Security Analysis:** This outage scenario was loaded into the N-1 Contingency Analysis module to verify that the grid remained resilient if a second line were to fail during the works, see Figure 65.

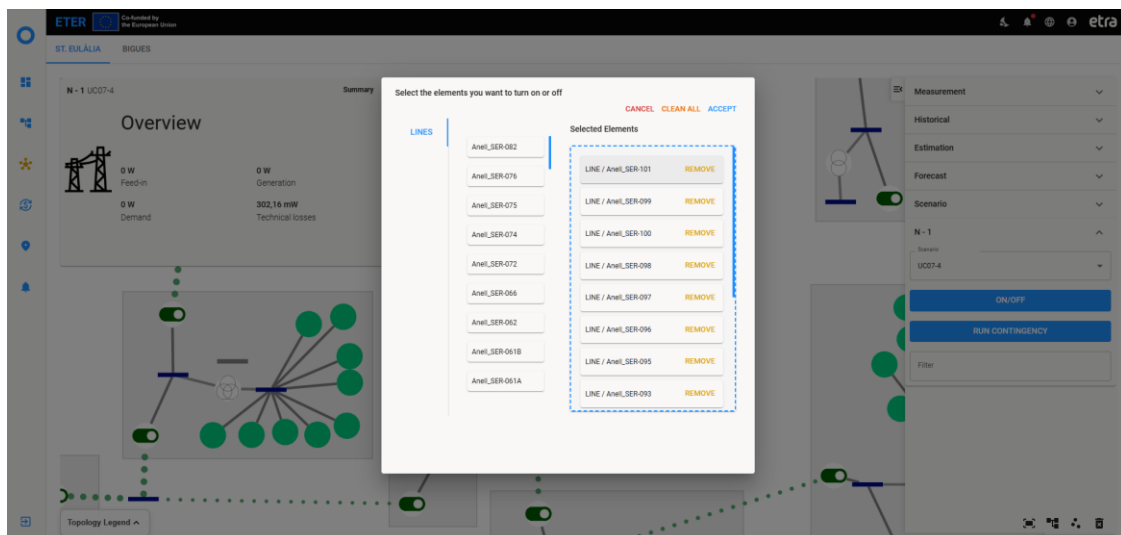


Figure 65. ETER GUI, N-1 Contingency Analysis module. CT-0265.

ETER generated sub-scenarios for every tested line to visualize the grid status after each potential second contingency, see Figure 66.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

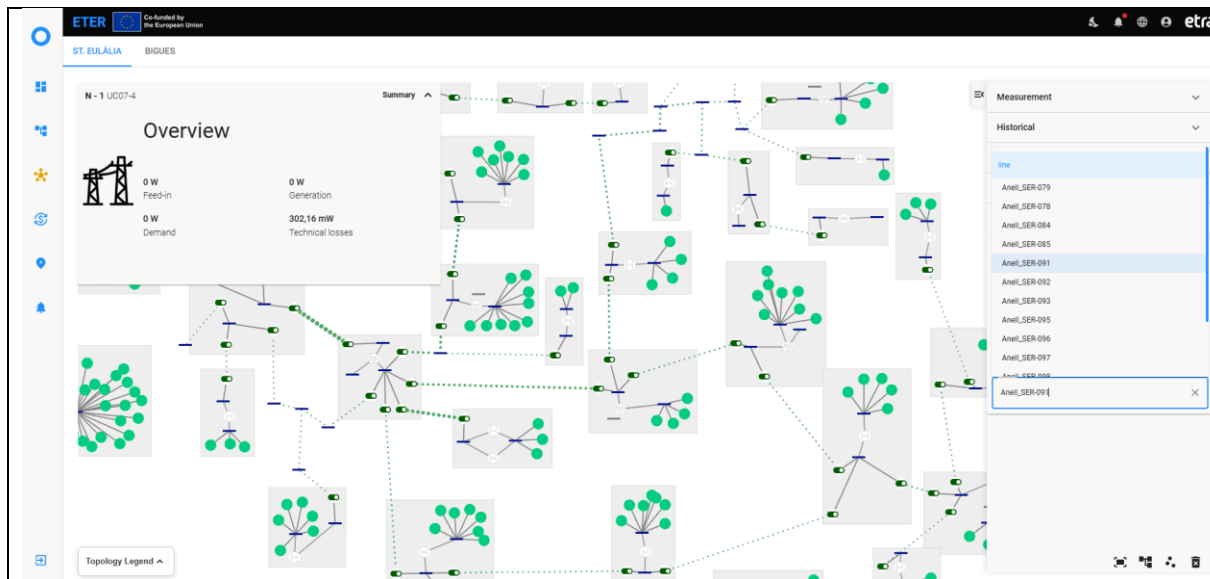


Figure 66. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0265.

An offline process executed the N-1 study for every hour of the forecast window for each substation, see Figure 67 and Figure 68 as examples, finding no operational violations or security issues for the planned maintenance.

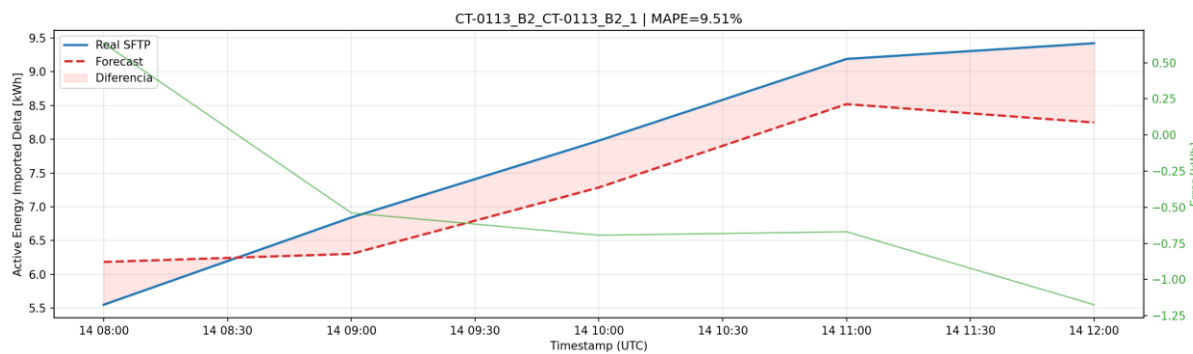


Figure 67. Forecast evolution of substation CT-0113 during maintenance.

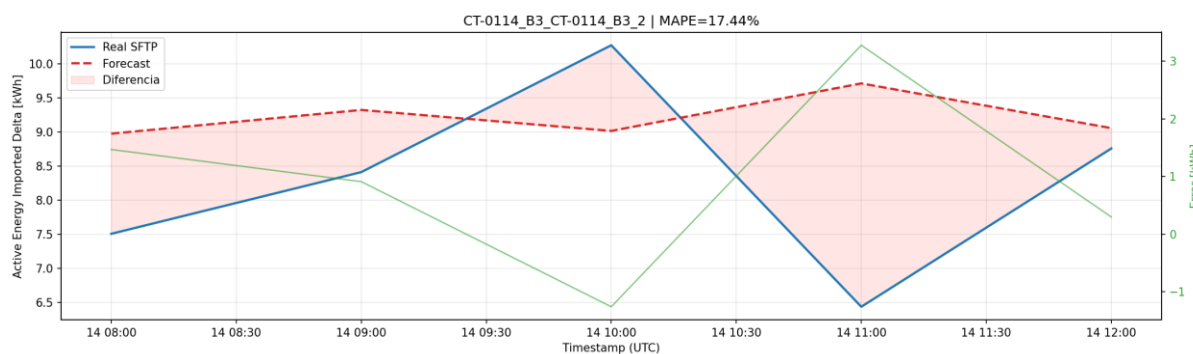


Figure 68. Forecast evolution of substation CT-0114 during maintenance.

During the actual work, a real-time process was used to monitor the grid. Because SCADA visibility is limited to specific substations, the system combined forecasts, SCADA data, and concentrator data to perform a continuous State Estimation and N-1 analysis, ensuring no power flow or stability problems occurred.

Finally, the real data from the concentrators was compared to the hourly predicted active power at each substation. As this is a regression problem, the accuracy was measured using MAPE (Mean

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Absolute Percentage Error), resulting in an average MAPE of 16.06% for the recalculated power flows considering 43 substations.

Qualitative assessment of the results

The test case successfully validated the ETER Digital Twin (DT) as a reliable tool for planning grid maintenance activities, specifically for substation CT-0620. The DT demonstrated its capacity to integrate load and generation forecasts, simulate power flow redistribution under outage conditions, and perform comprehensive N-1 contingency analysis to ensure grid resilience throughout the maintenance window.

The system successfully generated hourly forecasts for active power at 43 substations over the entire maintenance period, which were visualized through the ETER interface. This allowed operators to anticipate grid behaviour before the physical disconnection occurred and make informed decisions about the feasibility of the planned outage.

Scenario simulation was another key capability demonstrated during the test. By closing the switches associated with substation CT-0620 in the DT interface, a realistic outage scenario was created that accurately reflected the intended maintenance activity. The system automatically recalculated power flows and updated the grid state to reflect the new topology, confirming that no operational violations such as overloads or voltage violations would arise from the planned maintenance.

The N-1 contingency analysis provided an additional layer of security validation for the maintenance planning process. The DT executed an offline N-1 study for every hour of the forecast window across all substations, systematically evaluating the impact of each credible single contingency. This analysis verified that even if an additional line/substation failed during the maintenance works, the grid would remain secure and stable, with no security issues detected throughout the entire maintenance period.

Prediction accuracy was evaluated by comparing forecasted versus real concentrator data collected during the actual maintenance activity. Using Mean Absolute Percentage Error (MAPE) as the metric for this regression problem, the average MAPE across 43 substations was 16.06%. This indicates a reasonably accurate predictive performance for planning purposes.

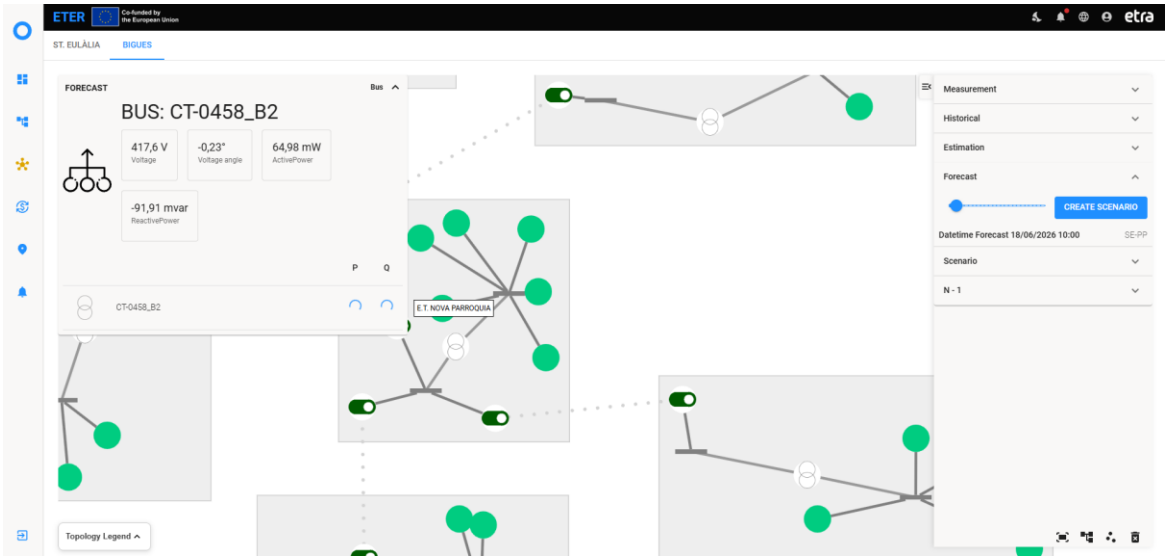
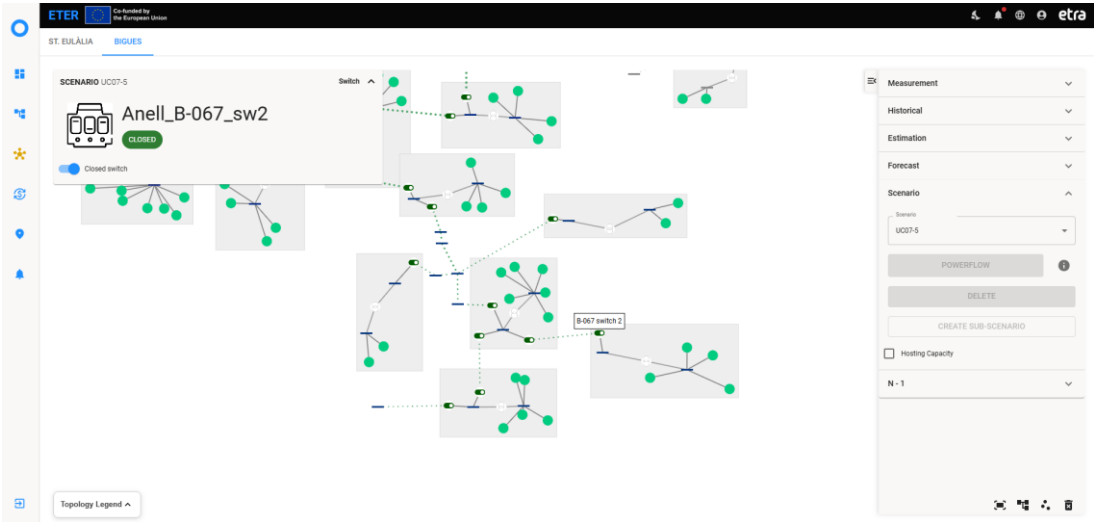
The test case confirmed that the ETER Digital Twin can create "what-if" scenarios that incorporate forecasted load and generation profiles, enabling proactive planning of maintenance activities with confidence. Operators can simulate switch operations to model line/substation disconnections and immediately observe the impact on power flows and grid stability, while the automated N-1 module evaluates all credible contingencies for each hour of the forecast window.

Table 38. Test case 5 for UC Ib07

Test Case ID	TC Ib07.5
Name	DT-based grid maintenance planning and N-1 assessment
Related UC	UC Ib07
Timeframe	18/06/2026 from 07:45h to 11:00h
Targets	Validate the Digital Twin (ETER) for planning grid maintenance activities (e.g., line disconnection for concrete pole installation). Perform load and generation forecasts for the outage period and

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

	execute N-1 contingency analysis to ensure the grid remains resilient during the maintenance. Calculate the accuracy of the DT predictions compared to real-world data using MAPE.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider, with a functionality to simulate forecasts, optimal power flows and N-1 contingency analysis.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. Smart meter data (exported and imported power).
Triggering Event	Scheduled maintenance for substation CT-0458
Pre-condition	• Network topology loaded and validated in ÉTER. • Forecasting and N-1 Contingency services deployed and integrated within the DT. Real-time SCADA and concentrator data streams active.
Experiment description	1) Identify the substation CT-0458 to be disconnected over the maintenance timeframe 18/06/2026 7:45h to 11:00h. 2) Generate forecasts in ETER for the maintenance window. 3) Run power-flow simulations for these forecast hours with the specific line out of service to identify potential issues. 4) Perform N-1 contingency analysis on the remaining network to ensure security of supply if another fault occurs during maintenance. 5) Save the forecasted power flow states. 6) Once maintenance occurs, gather real-time data. 7) Compare forecasted vs. real values.
Post-condition	Maintenance viability is validated. The grid is verified to be N-1 contingent during the outage. Forecast accuracy (MAPE) is calculated and stored.
Datasets required for the experiment	• MV network topology. • Forecasted load and generation profiles. Real-time SCADA and metering data recorded during the actual maintenance activity.
Field data to be gathered	• Forecasted power flow values (P, Q, V, I). • Real-time power flow values. • MAPE (Mean Absolute Percentage Error) of the deviation. List of operational violations (if any) during simulation.

Related KPIs	Ib07-KPI1: Accuracy in recalculated power flows.
Results of the experiment	
The experiment focused on a real maintenance operation: construction work on CT-0458, which required a scheduled outage from June 18th, 2026 (07:45) to June 18th, 2026 (11:00) The ETER tool allowed for a detailed simulation of this disconnection: Forecast Generation: Using the Forecast tab, a slider was used to select the specific hour to perform forecast, see Figure 69.	
	
Figure 69. ETER GUI, forecast tab. CT-0458. Scenario Creation: A specific scenario was created where the substation CT-0458 was disconnected by closing its respective switches in the Digital Twin interface, see Figure 70.	
	
Figure 70. ETER GUI, scenario switch closure. CT-0458. The scenario was then updated to analyse the resulting grid state and power flow redistribution, see Figure 71.	

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

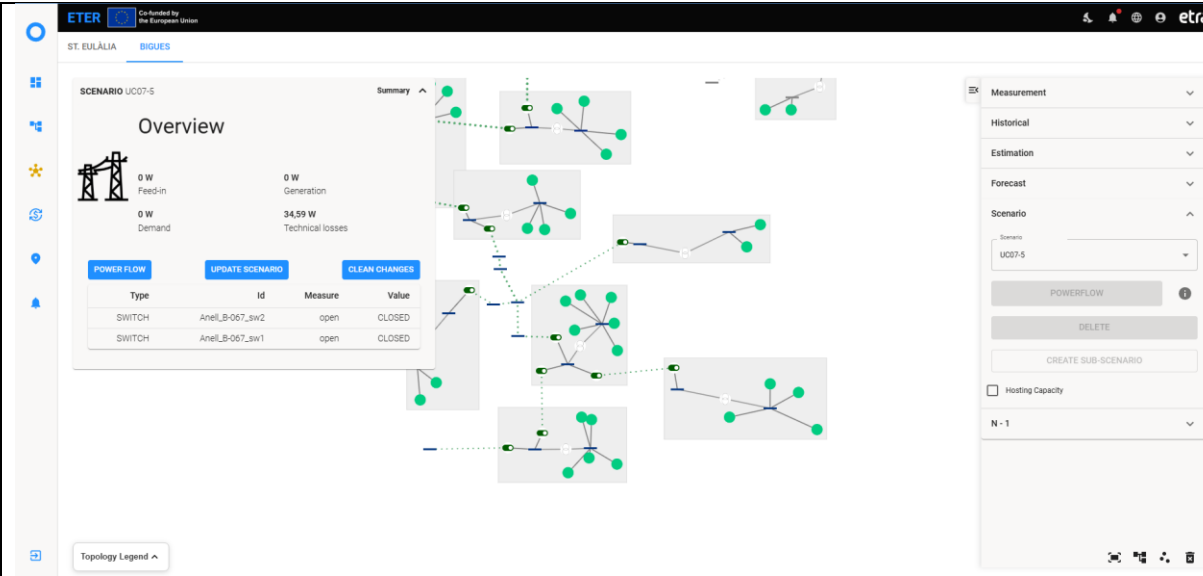


Figure 71. ETER GUI, scenario update with new changes. CT-0458.

- **N-1 Security Analysis:** This outage scenario was loaded into the N-1 Contingency Analysis module to verify that the grid remained resilient if a second line were to fail during the works, see Figure 72.

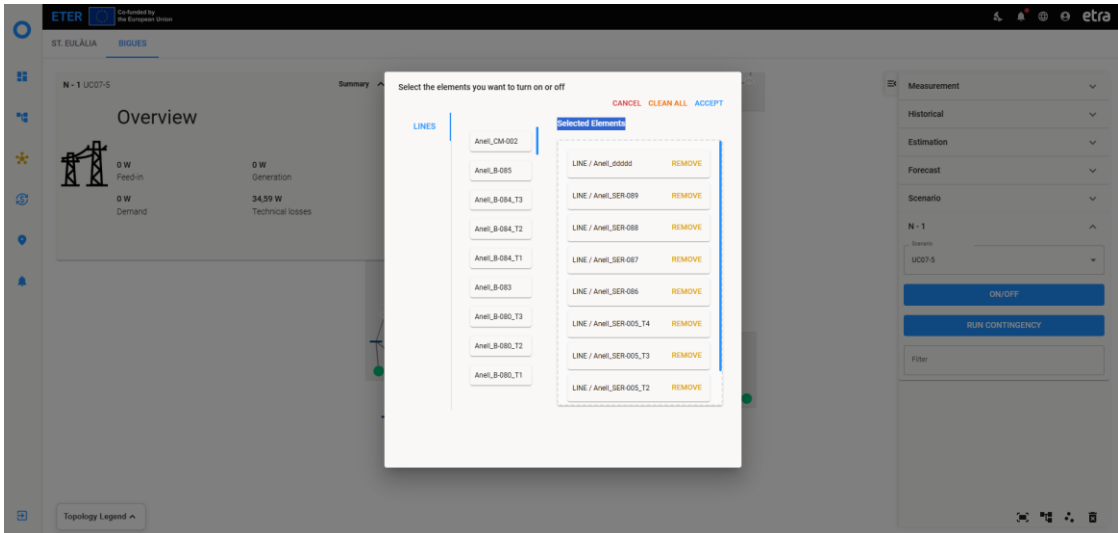


Figure 72. ETER GUI, N-1 Contingency Analysis module. CT-0458.

ETER generated sub-scenarios for every tested line to visualize the grid status after each potential second contingency, see Figure 73.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

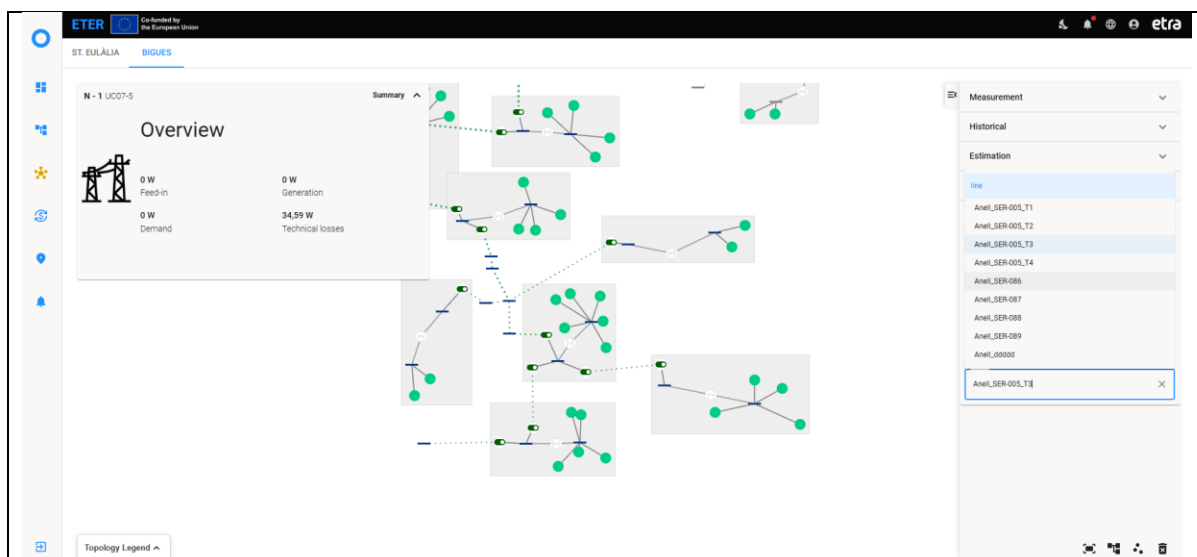


Figure 73. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0458.

An offline process executed the N-1 study for every hour of the forecast window for each substation, see Figure 74 and Figure 75 as examples, finding no operational violations or security issues for the planned maintenance.

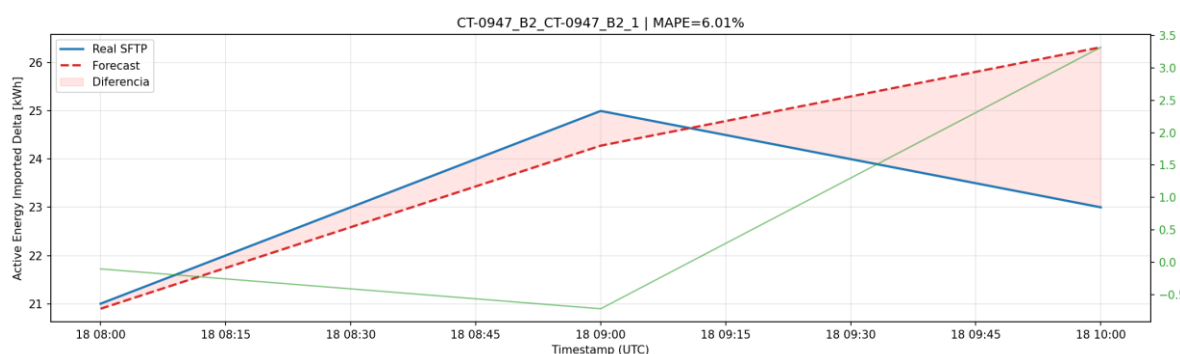


Figure 74. Forecast evolution of substation CT-0947 during maintenance.

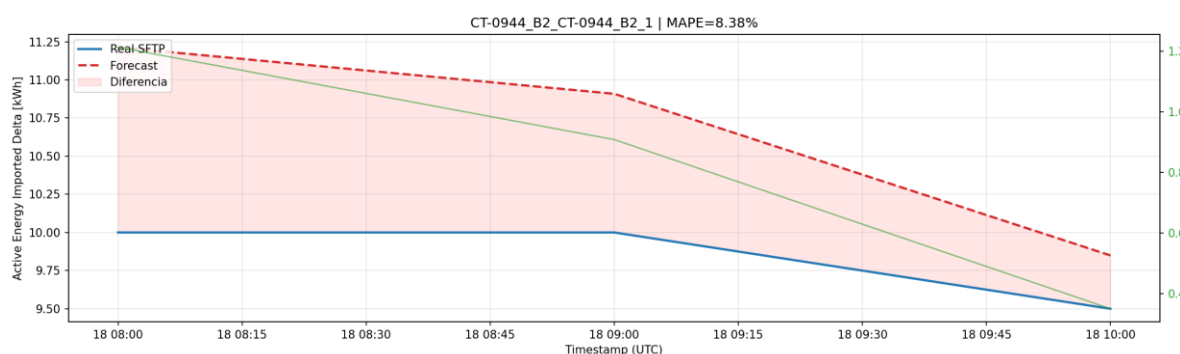


Figure 75. Forecast evolution of substation CT-0944 during maintenance.

During the actual work, a real-time process was used to monitor the grid. Because SCADA visibility is limited to specific substations, the system combined forecasts, SCADA data, and concentrator data to perform a continuous State Estimation and N-1 analysis, ensuring no power flow or stability problems occurred.

Finally, the real data from the concentrators was compared to the hourly predicted active power at each substation. As this is a regression problem, the accuracy was measured using MAPE (Mean

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Absolute Percentage Error), resulting in an average MAPE of 10.89% for the recalculated power flows considering 43 substations.

Qualitative assessment of the results

The test case successfully validated the ETER Digital Twin (DT) as a reliable tool for planning grid maintenance activities, specifically for substation CT-0458. The DT demonstrated its capacity to integrate load and generation forecasts, simulate power flow redistribution under outage conditions, and perform comprehensive N-1 contingency analysis to ensure grid resilience throughout the maintenance window.

The system successfully generated hourly forecasts for active power at 43 substations over the entire maintenance period, which were visualized through the ETER interface. This allowed operators to anticipate grid behaviour before the physical disconnection occurred and make informed decisions about the feasibility of the planned outage.

Scenario simulation was another key capability demonstrated during the test. By closing the switches associated with substation CT-0458 in the DT interface, a realistic outage scenario was created that accurately reflected the intended maintenance activity. The system automatically recalculated power flows and updated the grid state to reflect the new topology, confirming that no operational violations such as overloads or voltage violations would arise from the planned maintenance.

The N-1 contingency analysis provided an additional layer of security validation for the maintenance planning process. The DT executed an offline N-1 study for every hour of the forecast window across all substations, systematically evaluating the impact of each credible single contingency. This analysis verified that even if an additional line/substation failed during the maintenance works, the grid would remain secure and stable, with no security issues detected throughout the entire maintenance period.

Prediction accuracy was evaluated by comparing forecasted versus real concentrator data collected during the actual maintenance activity. Using Mean Absolute Percentage Error (MAPE) as the metric for this regression problem, the average MAPE across 43 substations was 10.89%. This indicates a reasonably accurate predictive performance for planning purposes.

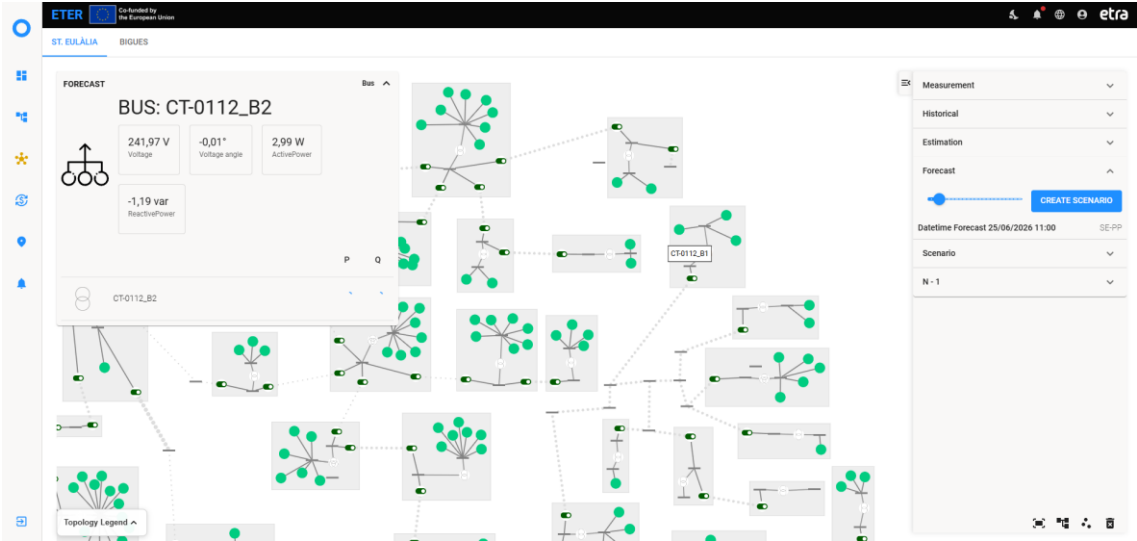
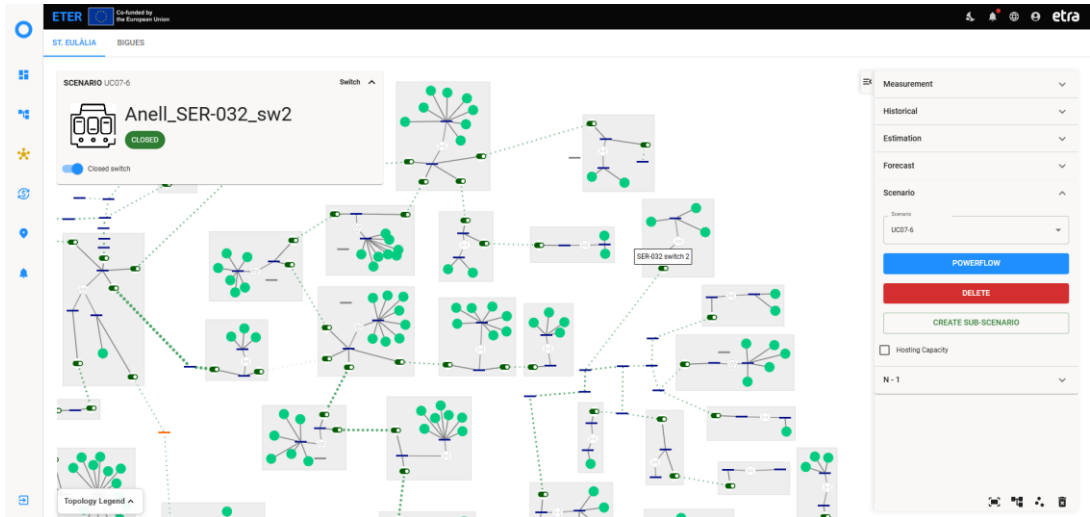
The test case confirmed that the ETER Digital Twin can create "what-if" scenarios that incorporate forecasted load and generation profiles, enabling proactive planning of maintenance activities with confidence. Operators can simulate switch operations to model line/substation disconnections and immediately observe the impact on power flows and grid stability, while the automated N-1 module evaluates all credible contingencies for each hour of the forecast window.

Table 39. Test case 6 for UC Ib07

Test Case ID	TC Ib07.6
Name	DT-based grid maintenance planning and N-1 assessment
Related UC	UC Ib07
Timeframe	25/06/2026 from 07:30h to 12:30h
Targets	Validate the Digital Twin (ETER) for planning grid maintenance activities (e.g., line disconnection for concrete pole installation). Perform load and generation forecasts for the outage period and

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

	execute N-1 contingency analysis to ensure the grid remains resilient during the maintenance. Calculate the accuracy of the DT predictions compared to real-world data using MAPE.
Actors involved	• ANELL - Grid Operator. It provides data (historical and real-time). • ETRA – ÉTER technology provider, with a functionality to simulate forecasts, optimal power flows and N-1 contingency analysis.
Assets and systems involved	• ETER • SCADA (P, Q, V, I) from the nodes. Smart meter data (exported and imported power).
Triggering Event	Scheduled maintenance for substation CT-0112
Pre-condition	• Network topology loaded and validated in ÉTER. • Forecasting and N-1 Contingency services deployed and integrated within the DT. Real-time SCADA and concentrator data streams active.
Experiment description	1) Identify the substation CT-0112 to be disconnected over the maintenance timeframe 25/06/2026 7:30h to 12:30h. 2) Generate forecasts in ETER for the maintenance window. 3) Run power-flow simulations for these forecast hours with the specific line out of service to identify potential issues. 4) Perform N-1 contingency analysis on the remaining network to ensure security of supply if another fault occurs during maintenance. 5) Save the forecasted power flow states. 6) Once maintenance occurs, gather real-time data. 7) Compare forecasted vs. real values.
Post-condition	Maintenance viability is validated. The grid is verified to be N-1 contingent during the outage. Forecast accuracy (MAPE) is calculated and stored.
Datasets required for the experiment	• MV network topology. • Forecasted load and generation profiles. Real-time SCADA and metering data recorded during the actual maintenance activity.
Field data to be gathered	• Forecasted power flow values (P, Q, V, I). • Real-time power flow values. • MAPE (Mean Absolute Percentage Error) of the deviation. List of operational violations (if any) during simulation.

Related KPIs	Ib07-KPI1: Accuracy in recalculated power flows.
Results of the experiment	
The experiment focused on a real maintenance operation: construction work on CT-0112, which required a scheduled outage from June 25th, 2026 (07:30) to June 25th, 2026 (12:30) The ETER tool allowed for a detailed simulation of this disconnection: Forecast Generation: Using the Forecast tab, a slider was used to select the specific hour to perform forecast, see Figure 76.	
	
Figure 76. ETER GUI, forecast tab. CT-0112. Scenario Creation: A specific scenario was created where the substation CT-0265 was disconnected by closing its respective switches in the Digital Twin interface, see Figure 77.	
	
Figure 77. ETER GUI, scenario switch closure. CT-0112. The scenario was then updated to analyse the resulting grid state and power flow redistribution, see Figure 78.	

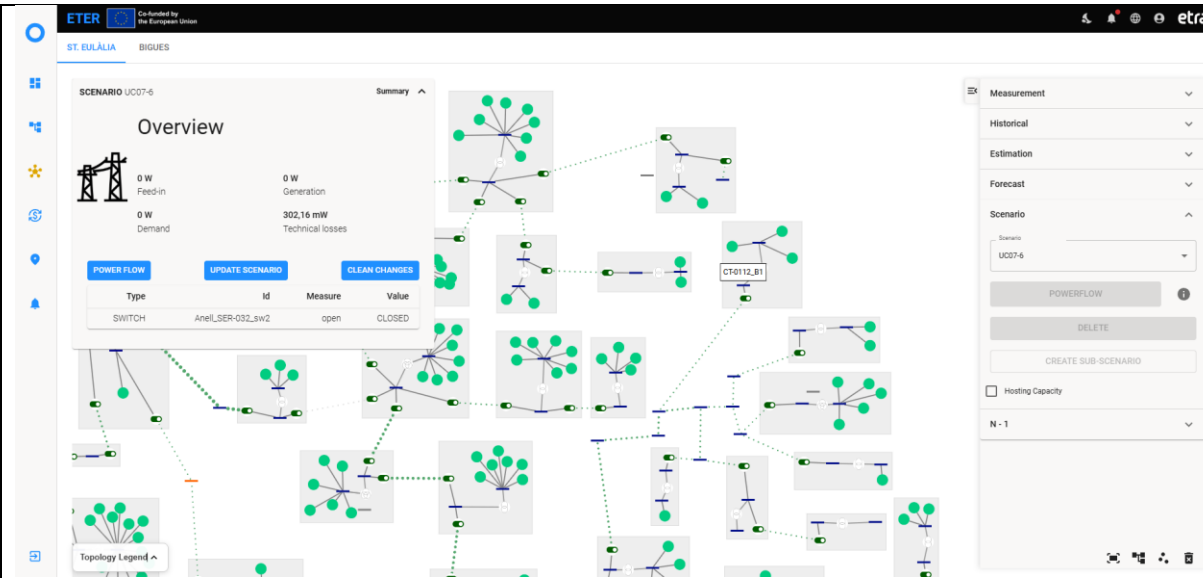


Figure 78. ETER GUI, scenario update with new changes. CT-0112.

- **N-1 Security Analysis:** This outage scenario was loaded into the N-1 Contingency Analysis module to verify that the grid remained resilient if a second line were to fail during the works, see Figure 79.

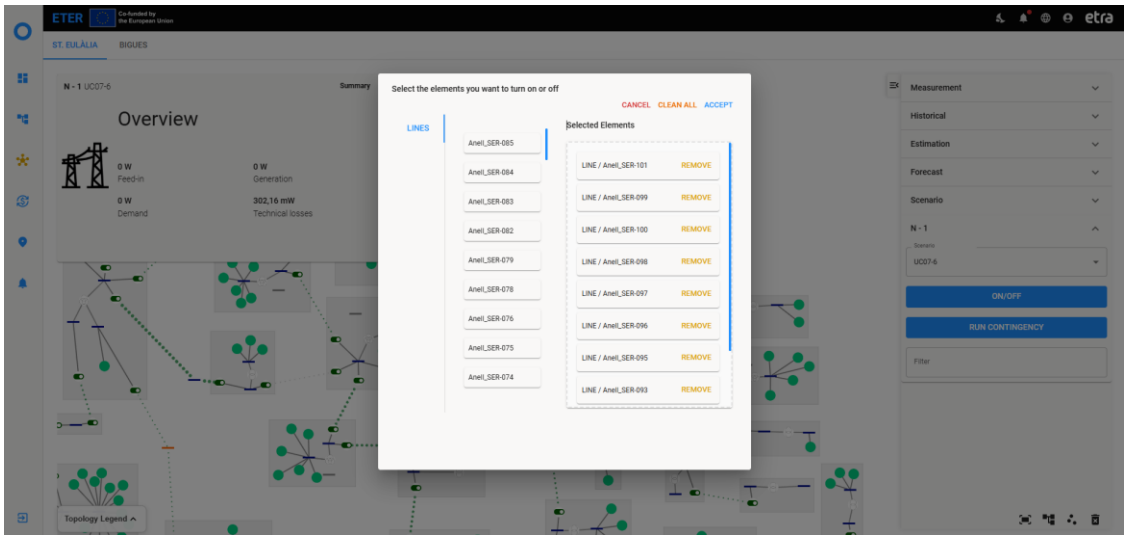


Figure 79. ETER GUI, N-1 Contingency Analysis module. CT-0112.

ETER generated sub-scenarios for every tested line to visualize the grid status after each potential second contingency, see Figure 80.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

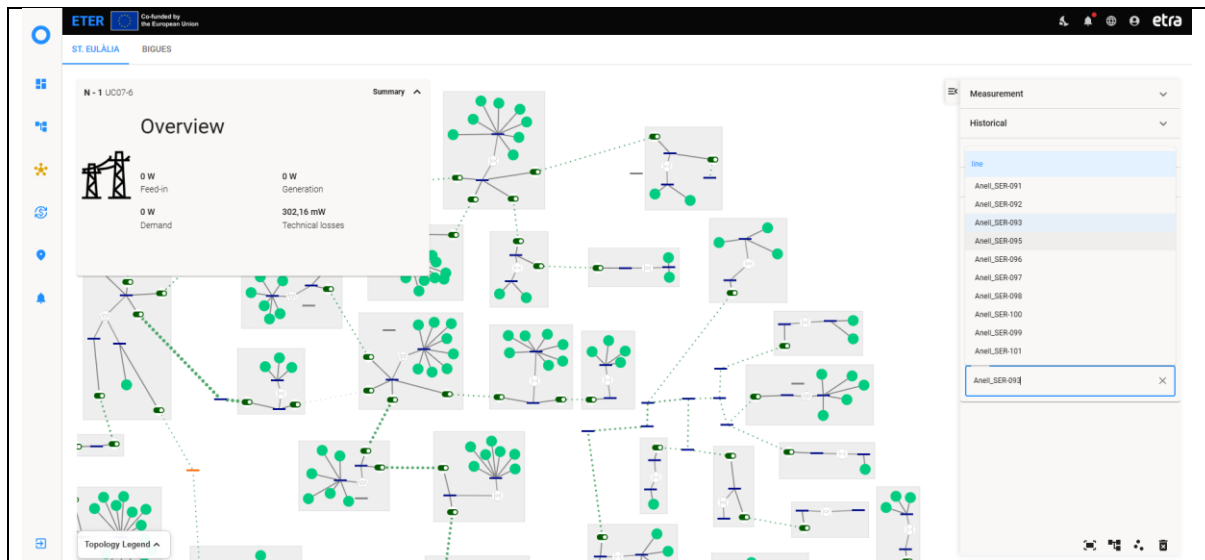


Figure 80. ETER GUI, N-1 Contingency Analysis subscenarios. CT-0112.

An offline process executed the N-1 study for every hour of the forecast window for each substation, see Figure 81 and Figure 82 as examples, finding no operational violations or security issues for the planned maintenance.

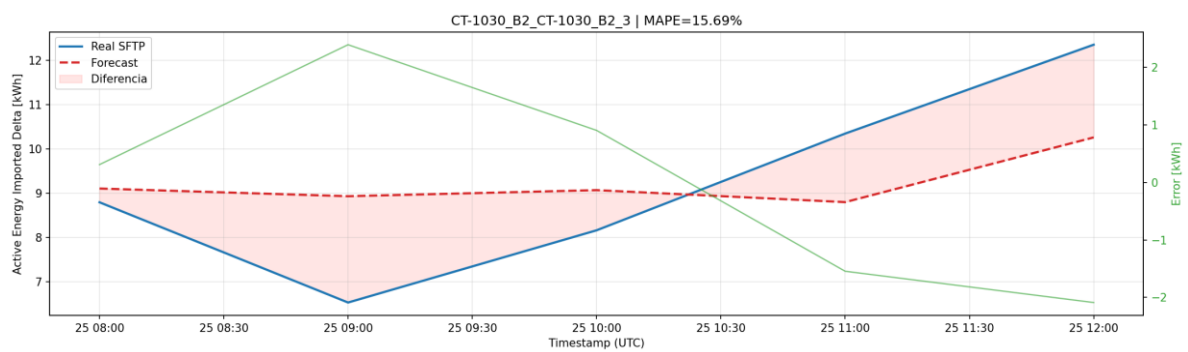


Figure 81. Forecast evolution of substation CT-1013 during maintenance.

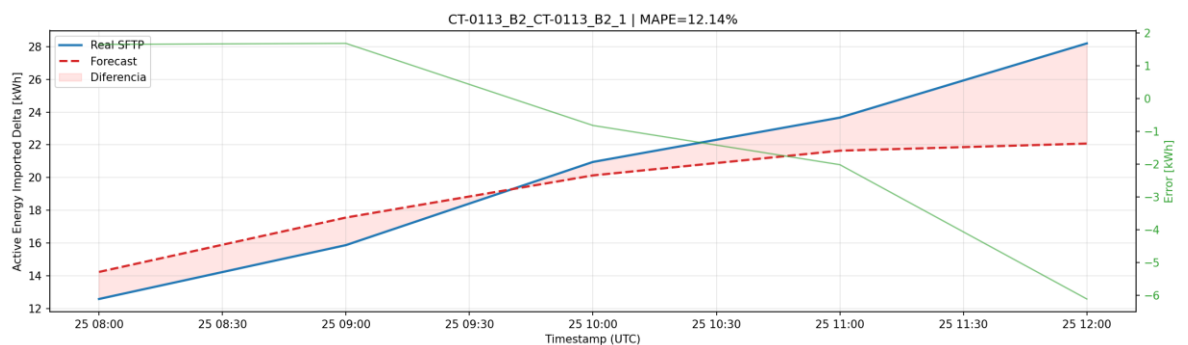


Figure 82. Forecast evolution of substation CT-0114 during maintenance.

During the actual work, a real-time process was used to monitor the grid. Because SCADA visibility is limited to specific substations, the system combined forecasts, SCADA data, and concentrator data to perform a continuous State Estimation and N-1 analysis, ensuring no power flow or stability problems occurred.

Finally, the real data from the concentrators was compared to the hourly predicted active power at each substation. As this is a regression problem, the accuracy was measured using MAPE (Mean

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

Absolute Percentage Error), resulting in an average MAPE of 11.15% for the recalculated power flows considering 43 substations.

Qualitative assessment of the results

The test case successfully validated the ETER Digital Twin (DT) as a reliable tool for planning grid maintenance activities, specifically for substation CT-0112. The DT demonstrated its capacity to integrate load and generation forecasts, simulate power flow redistribution under outage conditions, and perform comprehensive N-1 contingency analysis to ensure grid resilience throughout the maintenance window.

The system successfully generated hourly forecasts for active power at 43 substations over the entire maintenance period, which were visualized through the ETER interface. This allowed operators to anticipate grid behaviour before the physical disconnection occurred and make informed decisions about the feasibility of the planned outage.

Scenario simulation was another key capability demonstrated during the test. By closing the switches associated with substation CT-0112 in the DT interface, a realistic outage scenario was created that accurately reflected the intended maintenance activity. The system automatically recalculated power flows and updated the grid state to reflect the new topology, confirming that no operational violations such as overloads or voltage violations would arise from the planned maintenance.

The N-1 contingency analysis provided an additional layer of security validation for the maintenance planning process. The DT executed an offline N-1 study for every hour of the forecast window across all substations, systematically evaluating the impact of each credible single contingency. This analysis verified that even if an additional line/substation failed during the maintenance works, the grid would remain secure and stable, with no security issues detected throughout the entire maintenance period.

Prediction accuracy was evaluated by comparing forecasted versus real concentrator data collected during the actual maintenance activity. Using Mean Absolute Percentage Error (MAPE) as the metric for this regression problem, the average MAPE across 43 substations was 11.15%. This indicates a reasonably accurate predictive performance for planning purposes.

The test case confirmed that the ETER Digital Twin can create "what-if" scenarios that incorporate forecasted load and generation profiles, enabling proactive planning of maintenance activities with confidence. Operators can simulate switch operations to model line/substation disconnections and immediately observe the impact on power flows and grid stability, while the automated N-1 module evaluates all credible contingencies for each hour of the forecast window.

Table 40. Key Performance Indicator 1 for UC Ib07

KPI ID	Ib07-KPI1
KPI Name	Accuracy in recalculated power flows
Related Use Case	UC Ib07
KPI Description	Deviation between the expected behaviour of the grid forecasted by the DT for the period in which the maintenance activities will take place.

D8.2 Analysis of digital twin application for control centre support, technical restrictions resolution and operational planning

KPI Formula	$MAPE = \frac{1}{n} \sum_{t=1}^n \left \frac{Actual_t - Forecast_t}{Actual_t} \right \times 100 \%$
Variables explanation	<i>Actual_t</i> : Real active power value read at substation level <i>Forecast_t</i> : Forecasted active power value calculated at substation level
Unit of measurement	Percentage, %
Baseline	20%
KPI Value	10.89%
Reference signal(s)	n.a.
Comments	n.a.