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Deliverable D4.3

EVELIXIA Autonomous District Digital Twins

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Deliverable D4.3

EVELIXIA Autonomous District Digital Twins

Deliverable number	D4.3
Deliverable name	EVELIXIA Autonomous District Digital Twins
Lead beneficiary	UBE
Description	This deliverable is directly linked to the activities foreseen in Task 4.3 and Task 4.4, consolidating all foreseen technical developments on network awareness, forecasting and autonomous decision-making mechanisms at the district/grid level. This report is considered as the first version of D4.4.
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EXECUTIVE SUMMARY

The present deliverable reports on the development of the Autonomous District Digital Twin (ADDT) within the EVELIXIA Grid-to-Building (G2B) Services Framework. ADDT expands the Buildings as Active Utility Nodes (BAUNs) concept to district-scale applications, enabling validation of various scenarios in a virtual environment; the proposed framework targets to promote an automated decision-making processes for enhanced energy management, system planning, operation, and maintenance at the grid level.

The report outlines two coupled objectives. The first objective is the development of EVELIXIA's Network Awareness and Forecasting Framework (NAFF), featuring two Innovative Solutions (IS). The first one, namely the Multi-Vector Grids Energy Modelling and Simulation (IS15), provides a high-level intelligent Virtual Network (iVN) for city or community-level energy distribution simulations without requiring detailed physical grid models, thus enabling effective scenario testing and energy profiling. The second one, namely the Multi-Vector Smart Grid Maintenance Service (IS14), complements the district-level digital twin concept by extending the iVN capability to perform predictive maintenance analysis across multi-vector networks.

The second objective addresses the creation of EVELIXIA's Autonomous District Decision Support Framework (ANDSF), incorporating tools designed to support decision-making at the district and grid levels. The Grid Investment Planning Assistant Service (IS11) facilitates long-term strategic planning through proactive identification and evaluation of future network bottlenecks via comprehensive Cost-Benefit Analysis (CBA). The Multi-Vector Energy Network Manager Service (IS12) supports grid operators by effectively managing local congestion with flexibility-driven solutions that adhere to operational constraints. Additionally, the Aggregated Demand Portfolio Manager Service (IS13) enables energy aggregators to dynamically manage demand portfolios, aggregating building-level demand flexibility to actively participate in energy balancing markets.

The integration of NAFF and ANDSF results in a comprehensive digital twin framework, targeting the needs of grid/network operators, energy aggregators, utilities, and other actors managing multi-building portfolios.

The outcomes of the present deliverable correspond to the activities of Tasks 4.3 and 4.4 of WP4, as performed up to M18 of the project. The developed and reposted ISs demonstrate potential for replication across diverse network scenarios, with methodologies designed for adaptability, thanks to the generalization of models, coupled with multi-target simulation and data-driven methods.

This deliverable serves as the first milestone towards the development of the building blocks of the EVELIXIA services layer that will be deployed in real-world applications; in light of this, further steps towards the final version of the innovative solutions (up to M33) should focus on iterative engagement with grid-level actors of the project, including system operators and aggregators, to co-define scenario development and parameters' definition, as well as real-world data access. On the other hand, effort should be made to the successful integration of heterogenous data, multiple interconnected innovative solutions within the project and variable operational environments into compact solutions.

ABBREVIATIONS

Abbreviation	Name
ABDT	Autonomous Building Digital Twin
ADDT	Autonomous District Digital Twin
ANDSF	Autonomous District Decision Support Framework
BaU	Business-as-Usual
BAUNs	Buildings as Active Utility Nodes
BCR	Benefit-Cost Ratio
BESS	Battery Energy Storage Systems
CAPEX	Capital Expenditure
CBA	Cost-Benefit Analysis
DDT	District Digital Twin
DERs	Distributed Energy Resource(s)
DG	Distributed Generation
DR	Demand Response
DSO(s)	Distribution System Operator(s)
ETS	Emissions Trading System
G2B	Grid to Building
HI	Health Index
HP(s)	Heat Pump(s)
IS	Innovative Solution
iVN	i(ntelligent) V(irtual) N(etwork)
MV	Medium Voltage
LP	Linear Programming
LV	Low Voltage
NAFF	Network Awareness and Forecasting Framework
NPV	Net Present Value
NRA(s)	National Regulatory Authoritie(s)
OPEX	Operational Expenditure
PV	Photovoltaic
REG	Renewable Energy Generation
THD	Total Harmonic Distortion
ToU	Time-of-Use
TRL	Technology Readiness Level
TSO(s)	Transmission System Operator(s)

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1 INTRODUCTION AND OBJECTIVES

1.1 Scope and objectives

The main scope of the current deliverable is to report the development of the grid-equivalent Autonomous District Digital Twin (ADDT) under the EVELIXIA Grid-to-Building (G2B) Services Framework, allowing for validating different scenarios at the district level in a virtual testbed. ADDT extends the Buildings as Active Utility Nodes (BAUNs) vision to districts and aims to optimize energy management at a district scale.

In this context, two main objectives have been identified, as follows:

Objective 1: To develop the **EVELIXIA's Network Awareness and Forecasting Framework (NAFF)**. Towards this objective, a high-level district modelling tool for performing simulations of city/community-level energy distribution networks (intelligent Virtual Network – iVN, IS15) is built for the detailed network-level energy profiling, using energy conservation and power-flow analysis, across multiple energy vectors. A multi-vector smart grid maintenance service (IS14) is also developed to extend the capabilities of iVN engine, to assess the health level of multi-grid related assets, when connected to energy networks. The activities and progress of this objective is described in Section 2 of the present document.

Objective 2: To develop the **EVELIXIA's Autonomous District Decision Support Framework (ANDSF).** Towards this objective, the simulation capabilities of the iVN will be leveraged to create a set of decision-making and support services at the district/grid level, including the Grid Investment Planning service (IS11), the Multi-vector Network Management services (IS12) and the Aggregated Demand Portfolio Management services (IS13). These services focus on grid stakeholders (grid operators, energy aggregators, retailers, etc.), providing services from the Grid to the Building that could mutually benefit both sides. The activities and progress of this objective are described in Section 3 of the present document.

The interaction of the two objectives (frameworks) results in the EVELIXIA Autonomous District Digital Twin (depicted in Figure 1), aiming to cover the needs of Energy Aggregators, Utilities and any actor managing a portfolio of several building nodes.

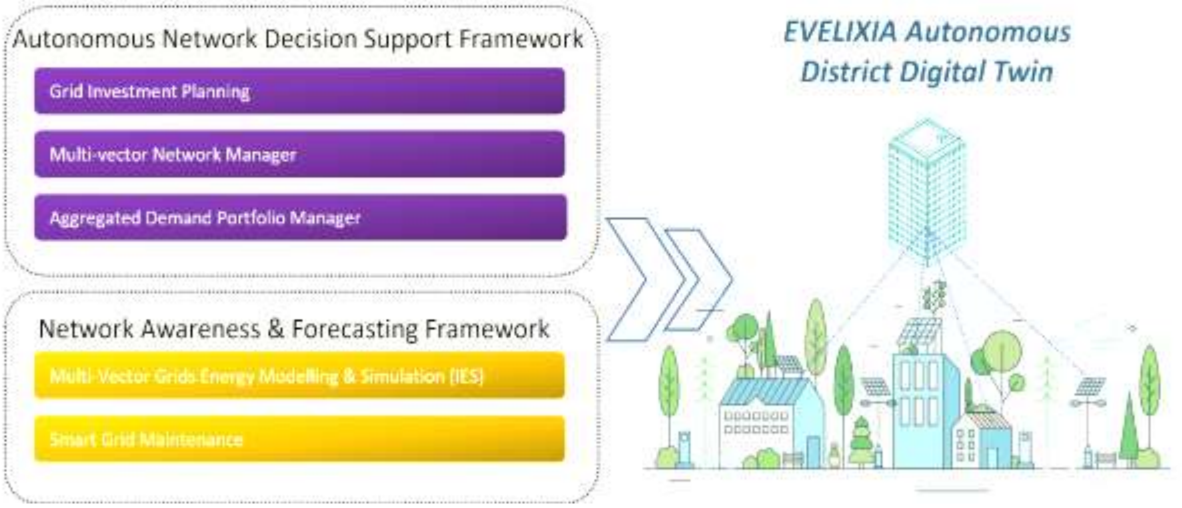

Figure 1. EVELIXIA Autonomous District Digital Twin Concept

1.2 Structure

The structure of the deliverable is as follows:

- Chapter 2 presents the work performed within T4.3 on the development and implementation of the Network Awareness & Forecasting Framework under the G2B Services Framework, highlighting its contribution to the broader EVELIXIA ADDT solution detailing the development of IS14 and IS15.
- Chapter 3 describes the work performed within T4.4 on the development of the innovative solutions IS11, IS12 and IS13, supporting the EVELIXIA ADDT framework.
- Chapter 4 summarizes the main conclusions for both tasks (T4.3 & T4.4) and discusses the future steps towards the next version of the present deliverable, i.e., by the end of the task in M33 of the project lifetime.

1.3 Relation to Other Tasks and Deliverables

D4.3 is directly linked to the activities foreseen in Task 4.3 and Task 4.4, consolidating all foreseen technical developments on situation awareness, forecasting and autonomous decision-making mechanisms at district and network levels. This report is considered as the first version of D4.4, which will focus on refining the context of the ISs developed in Tasks 4.3 and 4.4 according to the experience acquired from the pilots' implementation and tests' validation.

2 EVELIXIA'S NETWORK AWARENESS AND FORECASTING FRAMEWORK (NAFF)

The increasing complexity of modern energy systems, driven by the integration of diverse energy vectors (electricity, thermal, gas), the widespread adoption of distributed energy resources (DERs), and the evolving role of consumers as active participants in energy markets, necessitates advanced tools for network awareness and forecasting. Grid operators, energy aggregators, and utilities face significant challenges in ensuring efficient, resilient, and flexible energy systems capable of accommodating these dynamic changes. To address this, EVELIXIA's NAFF plays a pivotal role in enhancing situational awareness, enabling predictive maintenance, and supporting informed decision-making across multi-vector energy networks.

Chapter 2 reports the work performed within T4.3 on the development and implementation of the NAFF under the G2B Services Framework, highlighting its contribution to the broader EVELIXIA ADDT solution. The ADDT is designed to extend the BAUNs concept to the district level, fostering inter-building energy optimization and facilitating automated decision-making for holistic energy management. Unlike traditional digital twins that often require extensive digitization of physical grid assets, the EVELIXIA ADDT adopts a building-centric approach, leveraging aggregated building data, occupant patterns, utility signals, and DER integration to optimize energy exchanges and enhance overall system flexibility.

The chapter is structured as follows:

- **Section 2.1: Introduction** – Provides the context, objectives, and importance of the NAFF within the EVELIXIA project, including the interplay between the NAFF and the ANDSF.
- **Section 2.2: EVELIXIA District Digital Twin – Solution Design Overview** – Offers a detailed description of the ISs developed within T4.3 along their objectives, methodology, results and next steps.
    - **Section 2.2.1: Multi-Vector Grids Energy Modelling and Simulation solution (IS15)**
    - **Section 2.2.2: Multi-vector Smart Grid Maintenance service (IS14)**

2.1 Introduction

The global push for decarbonization, decentralization, and digitalization in energy systems is transforming the way energy networks are planned, operated, and maintained. The widespread adoption of DERs, the increasing participation of end-users in energy markets, and the growing complexity of multi-vector energy systems call for solutions that can deliver real-time awareness, accurate forecasting, and optimized decision-making.

Digital Twin (DT) technologies have emerged as a promising response to these challenges. Traditionally, DTs represent virtual replicas of physical assets, enabling simulations, real-time monitoring, and predictive analytics for enhanced operational efficiency. In the energy sector, DTs have been widely applied to model physical grids, offering valuable tools for asset management, grid planning, and fault detection. Leading technology providers, such as Siemens (PSS), GE Digital (Grid Solutions), OPAL RT, ALTAIR, and ANSYS, have developed comprehensive DT platforms supporting these applications. Several European Transmission System Operators (TSOs), including Finland's Fingrid and the Netherlands' TenneT, have implemented DT solutions to improve their grid operations, maintenance, and asset management processes.

Despite their effectiveness, conventional grid-focused DT solutions often require extensive data collection and detailed digitization of physical assets, which can be cost-prohibitive and complex to scale. Additionally, many existing platforms emphasize single-vector energy systems, overlooking the growing importance of multi-vector interactions and decentralized energy management at the district level.

Recognizing these gaps, the EVELIXIA project has developed an innovative approach through the EVELIXIA ADDT. Rather than focusing solely on the physical grid, the ADDT emphasizes building energy digital twins and aggregated district-level data to model energy exchanges and consumption patterns. This approach minimizes the need for extensive grid digitization while enabling accurate simulations and optimizations of multi-vector energy flows. The ADDT integrates information from buildings, DERs, occupant behaviors, utility signals, and weather forecasts to deliver comprehensive energy management services.

The ADDT is underpinned by the synergy between two core frameworks:

- **Network Awareness and Forecasting Framework (NAFF):** Provides capabilities for detailed energy profiling, predictive maintenance, and simulation across electricity, thermal, and gas networks.
- **Autonomous Network Decision Support Framework (ANDSF):** Utilizes data from the NAFF to support decision-making in grid investment planning, network management, and demand portfolio optimization.

This interplay enables a two-way, transactive energy system where buildings not only consume but also actively respond to grid signals, facilitating demand-side flexibility and improved energy efficiency across the district.

2.2 EVELIXIA district digital twin – Solution Design Overview

As mentioned above, T4.3 focuses on the development of the following ISs:

- Multi-Vector Grids Energy Modelling and Simulation solution (IS15): A high-level modeling tool that simulates energy distribution without requiring detailed physical grid modeling, enabling virtual testing of district-level control scenarios.
- Multi-Vector Smart Grid Maintenance Service (IS14) to assess the health of grid-related assets and supports predictive maintenance strategies.

These services are presented in detail in the following subsections.

2.2.1 Multi-Vector Grids Energy Modelling and Simulation solution (IS15)

The Multi-Vector Grids Energy Modelling and Simulation solution (IS15) developed by IES within the EVELIXIA project is based on the IES intelligent Virtual Network (iVN) software. The iVN is a high-level district modelling tool for performing simulations of city or community-level commodity distribution networks. Specifically, it performs Hierarchical Demand Aggregation and Supply Allocation; the iVN aggregates the demand for particular commodities, such as Electricity and Heat and allocates supplies (provision) to specific providers in order to meet the demand. The iVN can also perform physics simulations of PV panels, wind turbines and other renewable energy technologies, perform energy balance calculations, take into account existing storage provisions, track the use of Fuels and other Commodities (such as Water), estimate the impact of changes in tariffs and calculate CO_2 emissions associated with the direct consumption of fuels and the indirect CO_2 emissions resulting from the consumption of electricity, heat and cooling.

The main purpose of the iVN is to assist utility operators, policy makers and engineers with city or district-level decision making with regards to the supply and management of natural and man-made resources and the devices that make that possible. Specifically, it can inform users of the current performance of various utilities and quantitatively predict the impact of changes to city-infrastructure.

Unlike traditional urban-scale modelling tools, iVN employs a hybrid approach that combines 3D building geometry models with 2D schematic representations of energy distribution infrastructure. The software is designed to optimize energy distribution at a city/community level by aggregating demand and allocating loads to providers efficiently.

Within EVELIXIA, iVN is further enhanced to integrate real-time building energy demand data and digital twin instances, ensuring a bottom-up approach to urban-scale energy modelling. The key advancement is the ability to federate individual building digital twins into a platform-level digital twin, enabling a more holistic optimization strategy for energy networks.

2.2.1.1 Objectives

IS15 is designed to support network operators, urban planners, and policymakers by facilitating scenario-based analysis that enhances decision-making on energy distribution, flexibility, and infrastructure investments.

IS15 - Technical Objective: To transition from TRL5 to TRL7, IS15 will aim at improving its functionality, reliability, and real-world applicability. Initially designed as a high-level **district modelling tool**, the solution will be expanded to integrate real-time energy data from buildings, distribution networks, and external grid operators, ensuring a more dynamic and accurate representation of energy flows. A key enhancement involves the federated digital twin approach, where **multiple building-level models** will be aggregated to create a holistic district-wide simulation, capturing the complex interplay between various energy vectors. Additionally, IS15 will introduce **advanced automation mechanisms**, enabling periodic, physics-based simulations to run autonomously based on predefined triggers, minimizing the need for manual intervention. The platform's interoperability will also be reinforced through standardized data exchange protocols, allowing seamless integration with other EVELIXIA ISs, such as IS12 (Multi-Vector Network Manager) and IS14 (Smart Grid Maintenance Service). By embedding predictive analytics and demand-response modelling, IS15 will not only support energy planning but also enable real-time decision-making, ensuring that urban energy networks operate more efficiently and sustainably.

IS15 - Scientific Objective: Beyond its technical advancements, IS15 will contribute to **scientific research on urban energy modelling** by exploring **multi-vector interactions, predictive analytics, and decentralized energy management strategies**. A central focus of this research is to develop a deeper understanding of energy flow dynamics at the district level, assessing how different energy carriers—such as electricity, heat, and cooling—interact under varying conditions, including extreme weather events and peak demand fluctuations. The project will also investigate the **impact of integrating RES and flexibility mechanisms** on district-level energy stability, contributing to decarbonization efforts and regulatory policy development. The validation of IS15 in the pilot sites will provide a **real-world testbed** for these scientific developments, ensuring that the models and methodologies established can be effectively **replicated and adapted across different urban environments**.

2.2.1.2 Methodology

The IS15 development follows a structured methodology comprising three key phases:

1. **Data Integration & Model Development**
    - **Data Collection:** Real-time and historical data are collected from various sources, including building management systems (BMS), smart meters, weather forecasts, and operational grid data.
    - **Building Digital Twin Federation:** Individual building digital twins modelled within VE software in T4.1 are integrated into the iVN software to capture localized energy demand and generation profiles. This bottom-up approach ensures the aggregated district-level model accurately reflects building-level dynamics.
    - **Multi-Vector Network Model Construction:** Commodity networks (electricity, heat, cooling, water) are represented using a combination of

2D schematic infrastructures and 3D building geometries. These models account for physical constraints, technical specifications of generation units, storage devices, and energy conversion systems.

2. **Simulation & Optimization**
   - **Energy Flow Simulations:** Simulations are run to model energy flows across different vectors, considering demand-supply dynamics, weather conditions, and operational constraints. Advanced physics-based models are used for renewable generation technologies and storage units.
   - **Scenario Analysis:** Multiple control scenarios, including extreme weather conditions, equipment failures, and demand surges, are evaluated to assess network robustness and flexibility.
3. **Interoperability & Validation**
   - **Ontology Alignment:** To ensure seamless communication with other EVELIXIA components, standardized ontologies are used for data exchange, ensuring semantic interoperability.
   - **Pilot Implementation:** The Greek demonstration site serves as the initial validation environment, where simulations are compared against actual operational data to calibrate and refine models.
   - **Continuous Feedback Loop:** An iterative process ensures that simulation outcomes inform subsequent model adjustments, enhancing prediction accuracy and operational relevance.

2.2.1.3 Evaluation & Results

The evaluation phase of IS15 commenced with the Greek pilot site, focusing on a simplified yet representative model of the local electricity and heat networks. The goal of this initial phase was to validate the iVN platform's capabilities in aggregating building-level demands, integrating renewable energy generation, and simulating multi-vector energy flows at a district scale. Emphasis was placed on ease of implementation while ensuring sufficient granularity to inform decision-making processes.

The Greek pilot analyses 2 buildings, the Mpodosakeio Hospital and the CERTH/CPERI building, located in the Northwestern part of Ptolemaida city in Greece. Both buildings use district heating to cover their thermal loads, however, in Mpodosakeio a system of installed solar thermals of total power 625kWth is used (for solar cooling), while in CERTH building, photovoltaic panels with a power of 10 kW is utilized and an additional system of 38 kW is planned to be installed (for covering own electric loads). In the case study power line, 40-EORDEAS, there are 67 PV plants connected to the grid.

For the first iteration as a simplification of the grid, the simulation model was configured around three primary electricity demand nodes (represented in yellow in Figure 2):

- **Electric Node 1:** Aggregated electricity demand of all other energy users in the study area beyond the two targeted buildings.
- **Electric Node 2:** Represents the simulated electricity demand of the building modelled through digital twins developed in Task 4.1 (e.g., CERTH building using IS5 outputs).
- **Electric Node 3:** Captures the electricity demand of the local hospital facility (e.g., Mpodosakeio Hospital), given its significant and constant energy consumption profile.

Then, as the 2 buildings' thermal energy is covered by district heating, the heat network is represented by the red heat nodes in Figure 2.

To streamline the modelling process while maintaining accuracy, the following assumptions were adopted:

- **Node 1 Aggregation:** For this initial phase, Node 1 consolidates the total demand from all other consumers in the study area.
- **Network Configuration:** The network's schematic representation prioritizes elements critical to the analysis, with slight simplifications in the connection map that can be refined in subsequent phases if needed.
- **Photovoltaic (PV) Generation:** An aggregated PV node was included to represent the district's renewable electricity supply. This node assumes the following parameters:
    - 76 PV plants aggregated into a single generation node.
    - Efficiency of 20% for each PV system.
    - Total installed capacity of 9,710 kW with a uniform south-facing orientation.
- **Weather Data:** Simulations utilized an aggregated Athens weather profile, serving as a proxy for local climatic conditions affecting both demand and renewable generation.

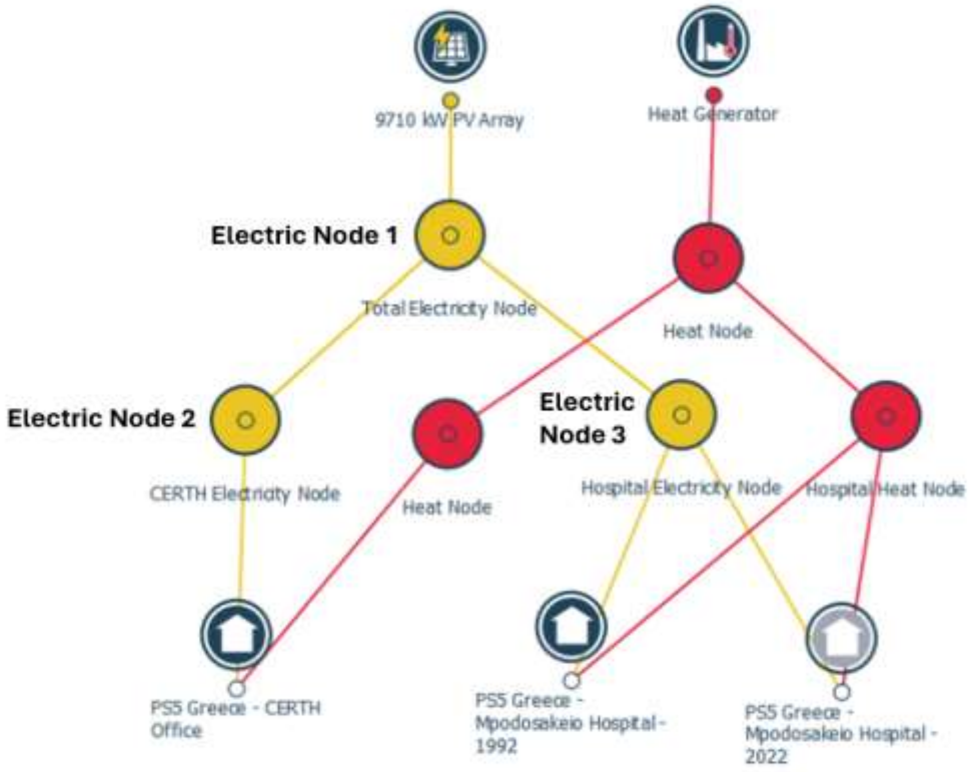

Figure 2. Greek Pilot District Digital Twin simplified model in iVN

Simulation Workflow and Methodology

The evaluation was conducted through a multi-step process:

1. **Building Digital Twin Development:** The two key buildings (CERTH and the hospital) were modelled using IS5, capturing detailed operational and occupant-driven demand profiles.
2. **Data Integration:** Simulated demand profiles from IS5 were imported into IS15 to establish accurate demand nodes within the district model.

Figure 3. Energy Demand profiles (Electricity and Heat) associated to Node 3 - Mpodosakeio Hospital within iVN

3. **Network Configuration:** A simplified iVN network was developed, incorporating the three demand nodes, the aggregated PV generation

node, and a connecting electricity node to simulate supply-demand interactions.

4. **Renewable Energy Integration:** The PV node was configured according to the assumptions listed above to assess the impact of local renewable generation on meeting district demand.
5. **Weather Data Application:** The model was subjected to hourly weather inputs derived from the Athens profile to reflect real-world variability in temperature, solar irradiance, etc..
6. **Output Generation and Data Export:** Simulation outputs were exported to the iSCAN platform, ensuring accessibility for project partners. The data included hourly readings in a tabular format covering:
    - Carbon emissions per node
    - Electricity demand (total and imported)
    - Electricity generated by PV systems
    - Heat demand for the relevant nodes

An example of the timeseries output in iVN can be seen in Figure 4 below.

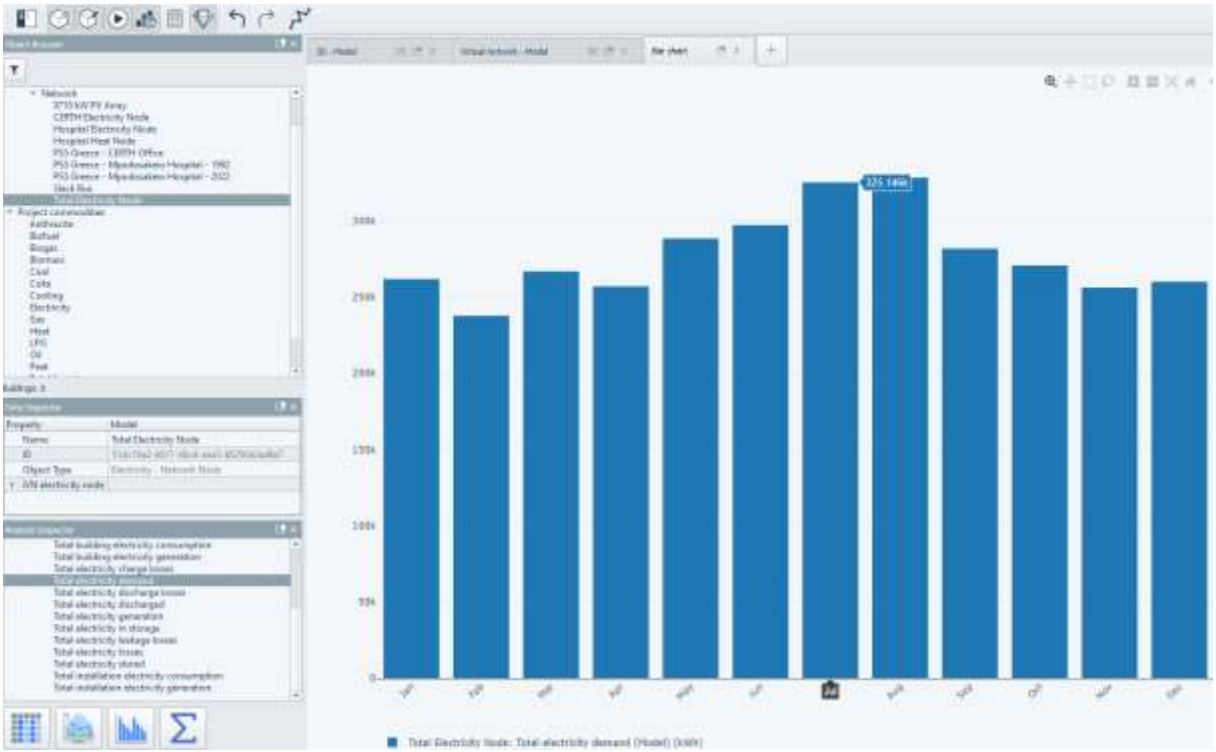

Figure 4. Total electricity demand per the total electricity node

Below in Figure 5 is an example of the iSCAN interface displaying simulation outputs. Users can interact with the data through customizable dashboards, filter by node, and compare demand and generation trends over selected timeframes.

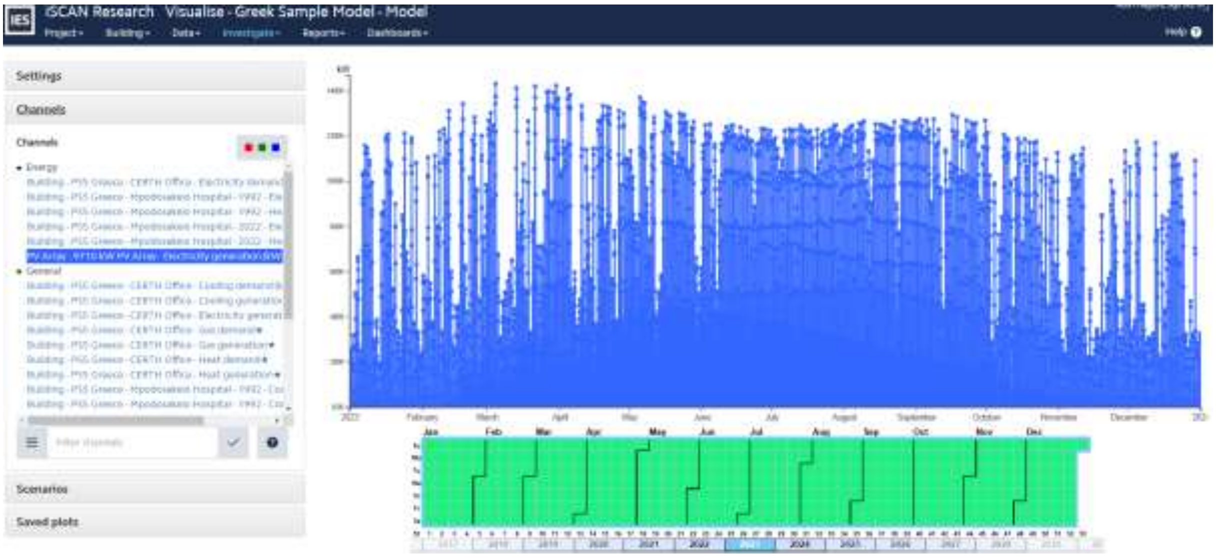

Figure 5. iVN simulated PV electricity generation viewed in iSCAN

2.2.1.4 Next steps

The next development steps for IS15 focus on expanding its capabilities through integration, testing, and validation in real-world scenarios. The following roadmap outlines key milestones:

1. **Model the Future Scenario of the Greek Pilot:** Implement the next phase of IS15 simulations at the Greek pilot site, incorporating additional real-world grid data and adding to the model the future assets that will be installed.
2. **Replicate the Methodology to Other Pilot Sites:** Apply the approach to the other pilot locations within the EVELIXIA framework, ensuring generalizability and adaptability to different urban contexts.
3. **Progress on Integration with Other ISs:**
   - **Establish connections between the DSM and the central data repository:** Ensure that IS15-generated data is fully synchronized with the EVELIXIA platform's central repository. Develop secure and automated data pipelines for continuous data transfer.
   - **Automate DSM output forwarding at required frequency:** Implement real-time DSM data transmission to ensure that IS15 can interact dynamically with other ISs and external grid operators.

- **Implement automated trigger for periodic dynamic simulation:** Develop and test an automated triggering mechanism that periodically initiates physics-based dynamic simulations based on predefined time intervals or grid state changes. Ensure that simulations operate autonomously and align with real-time network conditions.
- **Test and validate simulation trigger stability:** Conduct long-term performance tests to evaluate whether the automated simulation mechanism can maintain reliability and accuracy over extended periods.
- **Validate DSM output transfer to the Central Data Repository:** Perform integration testing to confirm that all DSM-generated data is being correctly archived and remains accessible for further analytics and decision-making.

By following this structured development plan, IS15 will enhance its effectiveness in urban energy modelling, predictive analytics, and demand-side management, ensuring its practical applicability across multiple pilot sites.

2.2.2 Multi-Vector smart grid maintenance service (IS14)

The increasing integration of multi-grid related assets, such as Battery Energy Storage Systems (BESS), photovoltaic (PV) systems, heat pumps (HPs), etc., into electrical networks requires a more efficient approach to maintain the reliability and efficiency of the electrical grid, considering Medium/Low Voltage (MV/LV) substations, and power lines maintenance planning. Traditionally, outage planning for maintenance has been executed using fixed time-based strategies, often leading to suboptimal scheduling, unnecessary maintenance, or failure to detect critical asset deterioration in time.

To address this challenge, the Smart Grid Maintenance Planning solution leverages live/real-time data collection, health assessment models, and predictive analytics to ensure that maintenance activities are planned proactively rather than reactively. This condition-based maintenance approach allows for early fault detection, extending grid-connected assets' life while minimizing disruptions and preventing catastrophic failures.

Furthermore, the tool integrates with a Digital Twin environment (for the project, the tool will be integrated with the iVN simulation engine), utilizing real-time/live sensor data to enhance maintenance decisions. By simulating assets' behaviour and predicting failure risks under different conditions, it provides actionable insights for proactive maintenance strategies, thus improving the reliability and efficiency of the grid.

The high-level overview of the tool is depicted in Figure 6.

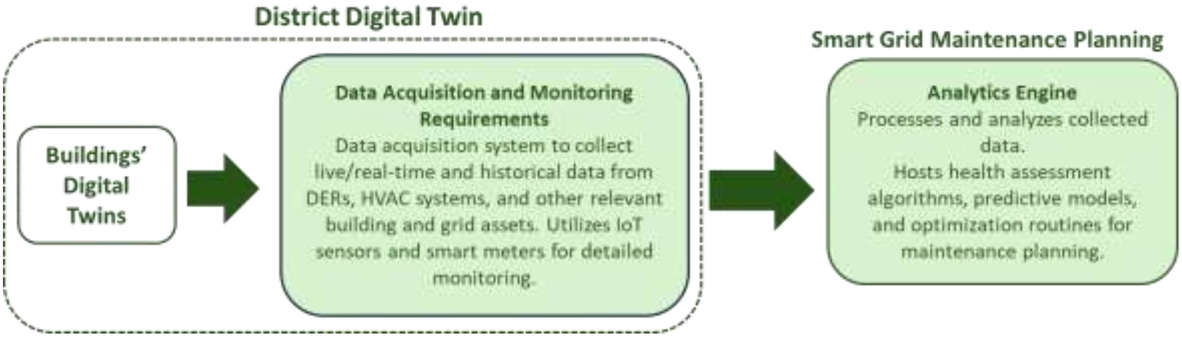

Figure 6. High-level overview of the smart grid maintenance tool

In summary, by shifting from static time-based maintenance to predictive and optimized scheduling, the tool enhances grid reliability, cost efficiency, and operational continuity for system operators.

2.2.2.1 Objectives

IS14 - Technical Objective "TRL5 to TRL7": With original functionalities developed and validated in the relevant environment of several past EU-funded projects (e.g. ONENET GA No. 957739) the Smart Grid Maintenance solution is introduced to EVELIXIA at TRL5. Advancing towards TRL6, a working version of IS14 is tested with simulated transformer datasets and artificial faults' injection, as it is further described in Section 2.2.2.3. The final version of IS14 will undergo validation using simulated or live data extracted by IS15 - "intelligent Virtual Network" (iVN) (see Section 2.2.1), ensuring applicability to each pilot site network under study. As part of EVELIXIA's platform integration, progressing towards TRL7 until the end of the project, future efforts and refinements of the tool target demonstration of the technology across EVELIXIA pilot sites, thus ensuring its applicability to support real-world smart maintenance outage planning for multi-grid related assets.

IS14 - Scientific Objective: The Smart Grid Maintenance Planning solution is designed to optimize maintenance scheduling for grid assets according to asset criticality and health condition, dynamically adjusting schedules to address higher-risk components promptly. Specifically, the solution targets at minimizing grid operational disruptions and improve efficiency in maintenance resource allocation, via mathematical-based optimization that coordinates maintenance tasks strategically, aligning relevant interventions with periods of low demand and utilizing DERs and building flexibility assets.

2.2.2.2 Methodology

The core component of the Smart Grid Maintenance Planning is the Analytics Engine, as depicted in Figure 7, integrating three discrete modules: data processing, health assessment, and optimization-based maintenance planning. These modules work in synergy to provide a proactive asset management approach for grids, facilitating informed decision-making and optimized maintenance scheduling, as described in the following paragraphs.

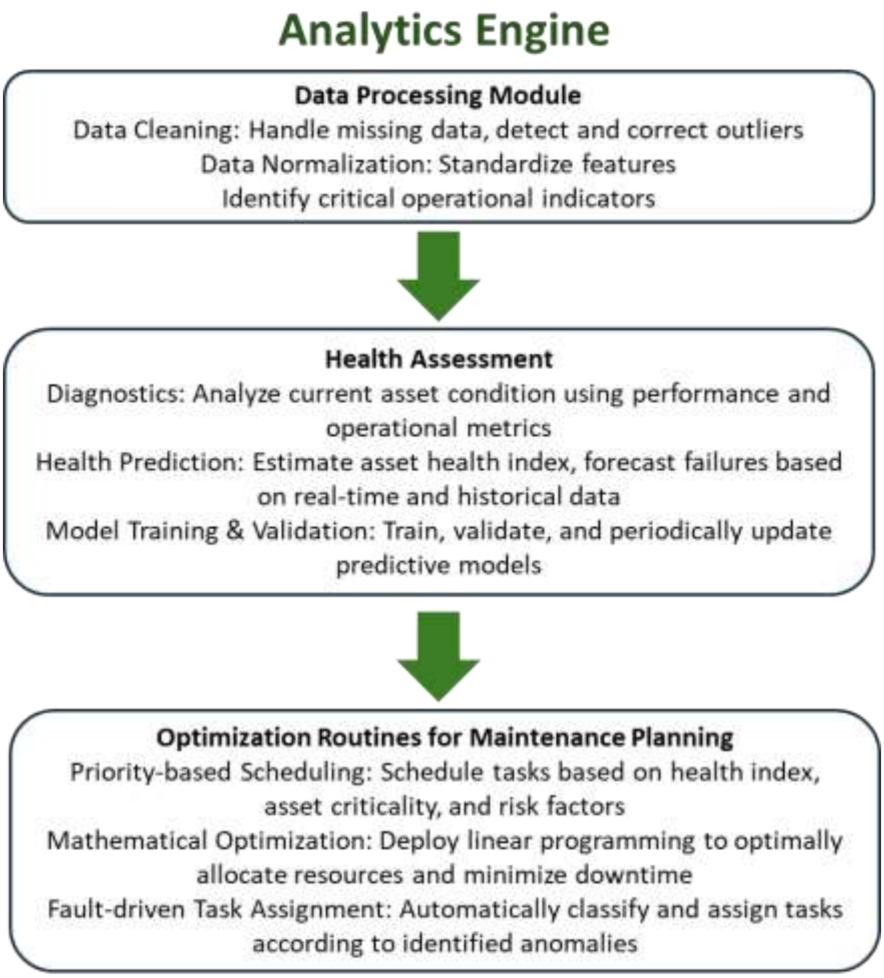

Figure 7. Smart Grid Maintenance Planning methodology – Analytics Engine

The first stage involves preprocessing and cleaning the incoming operational data streams, encompassing various parameters relevant to each asset. This step ensures data completeness, proper formatting, and suitability for subsequent analysis. The preprocessing includes handling missing data via imputation techniques, encoding categorical features appropriately, and identifying outliers indicative of potential asset faults. To ensure uniformity across features, z-score normalization [1] is applied as follows:

$$X' = \frac{(X-\mu)}{\sigma} \qquad \text{Eq.2.2.2.1}$$

where *X'* is the normalized data value, *X* is the raw input data, μ is the mean value of the feature across the dataset and σ is the standard deviation of the feature.

This normalization ensures that data features are standardized for use in predictive models.

Health Assessment

The tool deploys machine learning models for predicting asset health status of critical grid components. The predictive models use real-time sensor data and historical trends to assess degradation.

A general regression model for estimating asset Health Index (HI) can be expressed as follows:

$$HI_t = f(X_t) + \epsilon \qquad \text{Eq. 2.2.2.2}$$

where HI_t is the estimated Health Index at time *t*, *f(·)*[1] denotes the trained machine learning model that predicts asset HI based on operational features [2], X_t is the feature vector comprising asset-specific operational parameters (e.g., voltage,

[1] The choice of *f(·)* depends on the available data (size, quality, and historical depth) and computational constraints (real-time inference vs. batch processing) and accuracy requirements (interpretability vs. prediction precision). Linear regression is simple but limited in capturing nonlinear degradation. Random Forests provide high interpretability but may struggle with very large datasets. Gradient Boosting offers high accuracy but requires careful hyperparameter tuning. Neural Networks handle highly nonlinear relationships but require large training data.

current, temperature, etc.), and ϵ (epsilon) accounts for the model uncertainty (residual error term).

The estimation of HI is guided by asset-specific degradation factors which accelerate asset aging. A lower HI value indicates worsening asset condition, while a higher HI suggests the asset is in good health. Assets with HI values below a predefined threshold are prioritized for proactive maintenance scheduling.

To ensure that only relevant features are included in the health index estimation, a correlation-based feature selection approach is applied, based on the Pearson Correlation Coefficient Formula [3]. A correlation matrix for key operational parameters is computed to understand dependencies between the different operational features. Features with high positive correlation to degradation indicators negatively impact HI, whereas features with high negative correlation indicate operational stability

In real world implementation, the model is periodically retrained with updated datasets to dynamically adapt to evolving grid conditions, ensuring continuous improvement in HI predictions and maintenance prioritization.

Maintenance Scheduling Optimization

Once asset degradation is identified, the tool optimizes maintenance scheduling using Linear Programming (LP) to minimize service impact while ensuring that critical maintenance tasks are prioritized. The optimization problem is formulated as follows:

$$\min \sum_{i=1}^{N} \sum_{d=1}^{D} W_i x_{i,d} \qquad \text{Eq. 2.2.2.3}$$

where $x_{i,dx}$ is a binary decision variable (1 if maintenance task *i* is scheduled on day *d*, 0 otherwise), W_i is the task priority weight, computed as follows:

$$W_i = \frac{1}{HI_i} P_i \qquad \text{Eq. 2.2.2.4}$$

where HI_i reflects asset condition urgency (lower HI means the asset is closer to failure), and P_i represents the criticality score quantifying the asset's impact on grid reliability.

N represents the number of assets under study, while *D* represents the number of days in the scheduling horizon.

The optimization problem is subject to the following constraints:

- Each maintenance task is scheduled exactly once:

$$\sum_{d=1}^{D} x_{i,d} = 1, \forall\, i \in N \qquad \text{Eq. 2.2.2.5}$$

- Maximum number of maintenance tasks per day:

$$\sum_{i=1}^{N} x_{i,d} \leq M, \quad \forall\, d \in D \qquad \text{Eq. 2.2.2.6}$$

where M represents the maximum number of maintenance tasks that can be executed per day due to resource constraints.

- Task scheduling constraint within the planning horizon:

$$x_{i,d} \in \{0,1\}, \quad \forall\, i, d \qquad \text{Eq. 2.2.2.7}$$

The solution to this optimization problem provides an optimal maintenance schedule that ensures the most critical tasks are executed first while balancing operational constraints.

To improve scheduling efficiency, maintenance tasks are classified based on the detected anomalies. This ensures that each failure type is matched with an appropriate maintenance intervention (e.g., cooling system maintenance for assets with overheating anomalies, such as high winding temperatures in transformers, etc.). Different grid assets experience distinct degradation mechanisms, thus asset-specific classification rules must be adapted accordingly.

Additionally, to further refine priority scores, correlation analysis is introduced to adjust maintenance urgency based on feature dependencies. The revised task priority weight can be formulated as follows:

$$W_i{}' = W_i(1 + \sum_j C_{i,j}) \qquad \text{Eq. 2.2.2.8}$$

where $C_{i,j}$ denotes the absolute correlation between the operational parameter i and other grid health indicators. This ensures that maintenance urgency increases when the asset’s degradation is linked to multiple failure-related variables.

2.2.2.3 Evaluation & Results

To validate the operation of the smart grid maintenance tool, a test-run is conducted on simulated transformer datasets. This process ensures that real-time and historical asset data are structured, analyzed, and validated before moving to predictive modeling and optimization-based maintenance scheduling. It is noted that in this deliverable, only electricity network components are examined, although the methodology can be applicable to assets related with multi-energy networks, if such data is available.

The dataset used for this validation reflects real-world operational conditions of two MV/LV distribution transformers (namely Transformer 2 and Transformer 3). It consists of hourly measurements over a defined period and includes both normal operation data and artificial faults to evaluate the tool's ability to detect anomalies and optimize maintenance actions. The recorded parameters include operational variables that can be measured from actual transformers, such as Voltage (V), Current (A), Active Power (kW), Reactive Power (kVAR), Apparent Power (kVA), Power Factor, Frequency (Hz), Total Harmonic Distortion (THD, %), Ambient Temperature (°C), Winding Temperature (°C), Oil Temperature (°C), Energy Consumption (kWh) and Load Profile (%). The injected faults include overheating events where the winding temperature exceeds 90°C, voltage drops where voltage falls below 210V (reflecting the European grid’s nominal 230V voltage levels), and power quality issues characterized by THD levels above 7%. These fault conditions mimic real grid disturbances and stress conditions that impact transformers’ health, thus allowing to assess the effectiveness of the anomaly detection and maintenance optimization processes.

The reason for including two transformers for this test-case is to prove the tool’s ability to analyze and optimize maintenance scheduling for several grid components, as is the real case. In the test-run, each transformer's dataset is processed independently, ensuring that transformer-specific degradation trends and failure risks are accurately captured.

Before using the dataset for predictive modeling, a preprocessing step was applied to clean and structure the data. Missing values were handled appropriately: numerical values were filled with zeros where applicable, while categorical and timestamp values were interpolated using previous data points to maintain continuity. Timestamps were formatted consistently to ensure proper time indexing for trend analysis.

Additionally, several condition indicators were derived to enhance the dataset's analytical value. The health status was estimated based on the thermal stress impact on the transformer, using deviations in winding and oil temperature from nominal values[2] [4], [5]. The criticality score was dynamically scaled based on voltage stability and load profile, while a priority index was assigned based on Health Index [6] ensuring that assets closer to failure received higher maintenance urgency.

The results from this data processing are presented in Figure 8, Figure 9, Figure 10, Figure 11, Figure 12 and Figure 13.

[2] Transformer aging is predominantly driven by thermal stress, particularly due to high winding temperatures. The insulation system inside transformers degrades over time due to heat exposure, reducing the ability to withstand electrical and mechanical stresses. According to IEEE Std. C57.91-2011 and IEC 60076-7, insulation aging is exponentially related to temperature. Thermal models, such as the Arrhenius equation and IEEE aging formulas, suggest that the rate of degradation doubles for every 6-8°C increase in winding temperature above the reference operating condition (typically 110°C for oil-immersed transformers). The loss of insulation life can be estimated based on the cumulative effect of overheating. The HI estimation formula is derived from the thermal deviation of winding and oil temperature from nominal operational values, following a linear degradation approach, where each degree of overheating reduces the remaining insulation life. This aligns with transformer health assessment methodologies used in predictive maintenance.

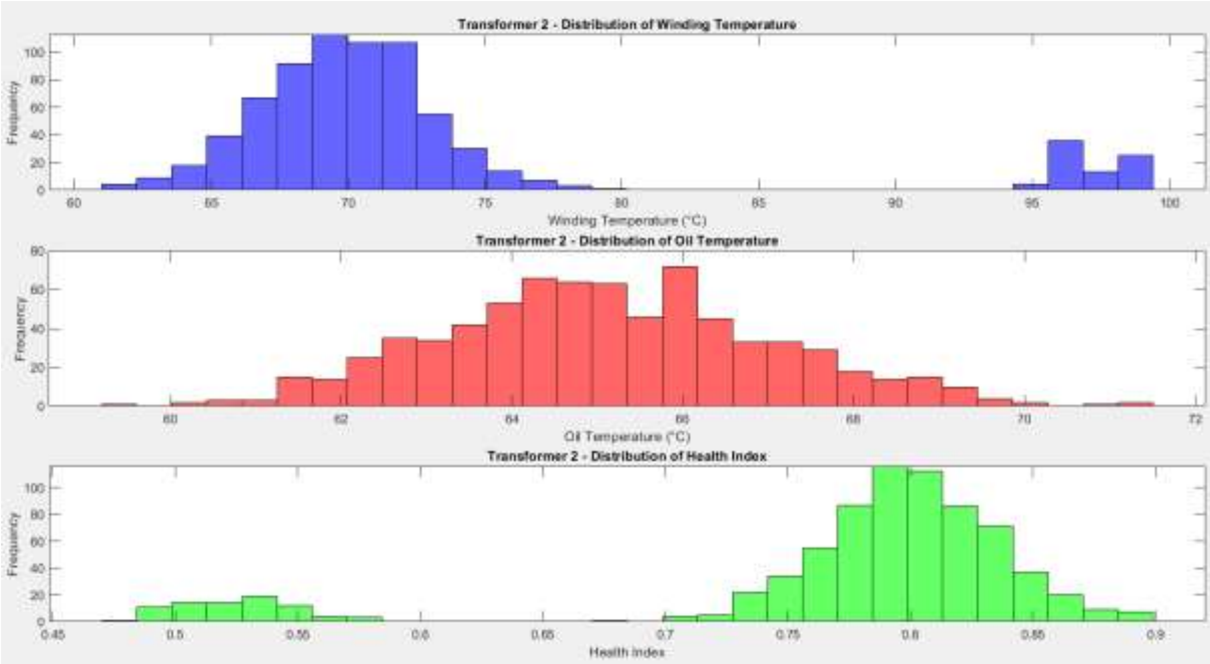

Figure 8. Distribution of different parameters' values based on the simulated datasets for transformer 2

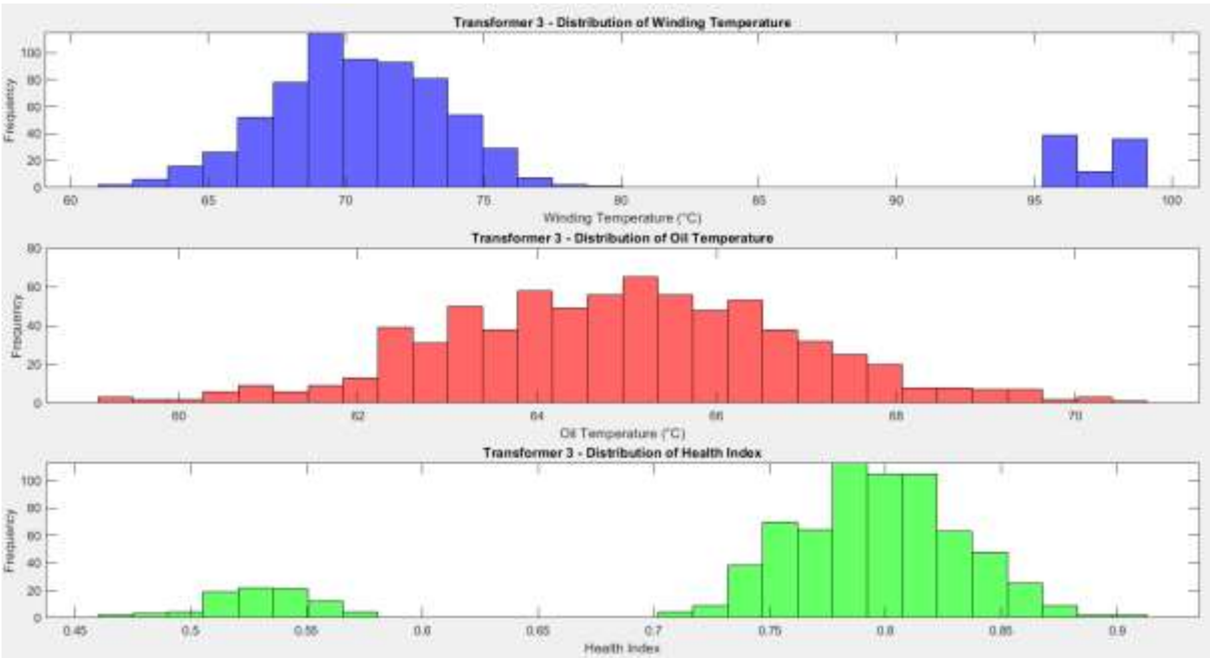

Figure 9. Distribution of different parameters' values based on the simulated datasets for transformer 3

Regarding Figure 8 and Figure 9, it can be observed that the winding temperature for Transformer 2 ranged from 61.25°C to 99.39°C, while Transformer 3 exhibited values between 61.22°C and 98.85°C. Peak temperatures exceeding 95°C indicate potential overheating risks, warranting close monitoring. The oil temperature for Transformer 2 varied between 59.25°C and 71.32°C, while for Transformer 3, it ranged from 59.34°C to 70.72°C. Although oil temperature remained relatively stable, its correlation with winding temperature fluctuations suggests thermal stress accumulation.

Calculated HI values confirmed these observations. Transformer 2 presented HI values from 0.61 to 0.99, while Transformer 3 ranged from 0.47 to 0.91. Lower HI scores approaching 0.5 suggest substantial health degradation, signaling a need for timely intervention and proactive maintenance[3] [7].

Moreover, the temperature histograms for the two transformers depicted in Figure 10 and Figure 11 present clear signs of overheating, particularly in winding temperature distributions. Time-series trend plots highlighted frequent and sharp spikes in winding temperature, indicative of severe load fluctuations.

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[3] Industry standards indicate that transformers typically have a design life of 25-40 years, but this is contingent on normal operating conditions. However, actual transformer lifespan is significantly impacted by operational stresses, particularly thermal conditions. Transformers exhibiting a Health Index (HI) of 0.5 or lower represent advanced degradation stages, signaling substantial insulation deterioration and reduced reliability. Assets in this range necessitate close monitoring, timely preventive maintenance, or strategic planning for replacement to prevent failure. Following guidelines such as C57.91-2011 (IEEE) and IEC 60076-7, transformers showing continuous deviations from nominal thermal conditions, reflected in low Health Index values, must be prioritized for intervention to avoid catastrophic failures and minimize the risk of unplanned outages.

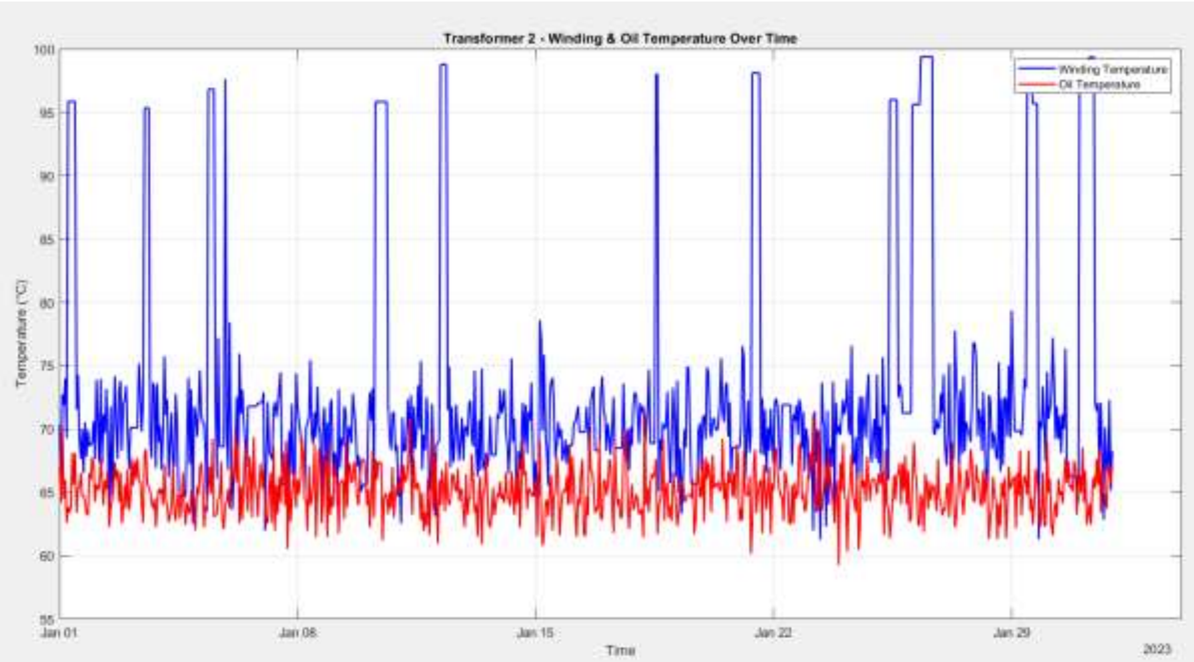

Figure 10. Temperature histogram based on the simulated datasets for transformer 2

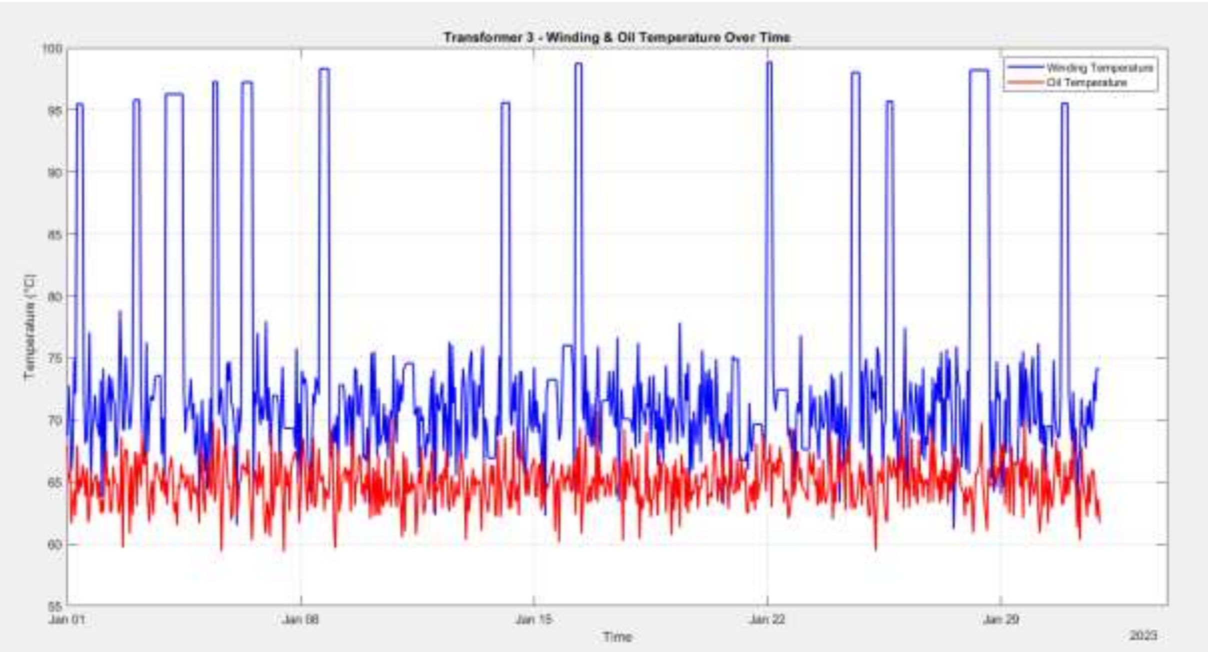

Figure 11. Temperature histogram based on the simulated datasets for transformer

Furthermore, the three-dimensional scatter plots in Figure 12 and Figure 13 illustrate the relationship between voltage, load profile, and criticality score demonstrating how high load stress and voltage fluctuations contribute to increased criticality scores. This visualization is particularly useful in identifying transformers under severe operational stress that may require prioritization in maintenance schedules.

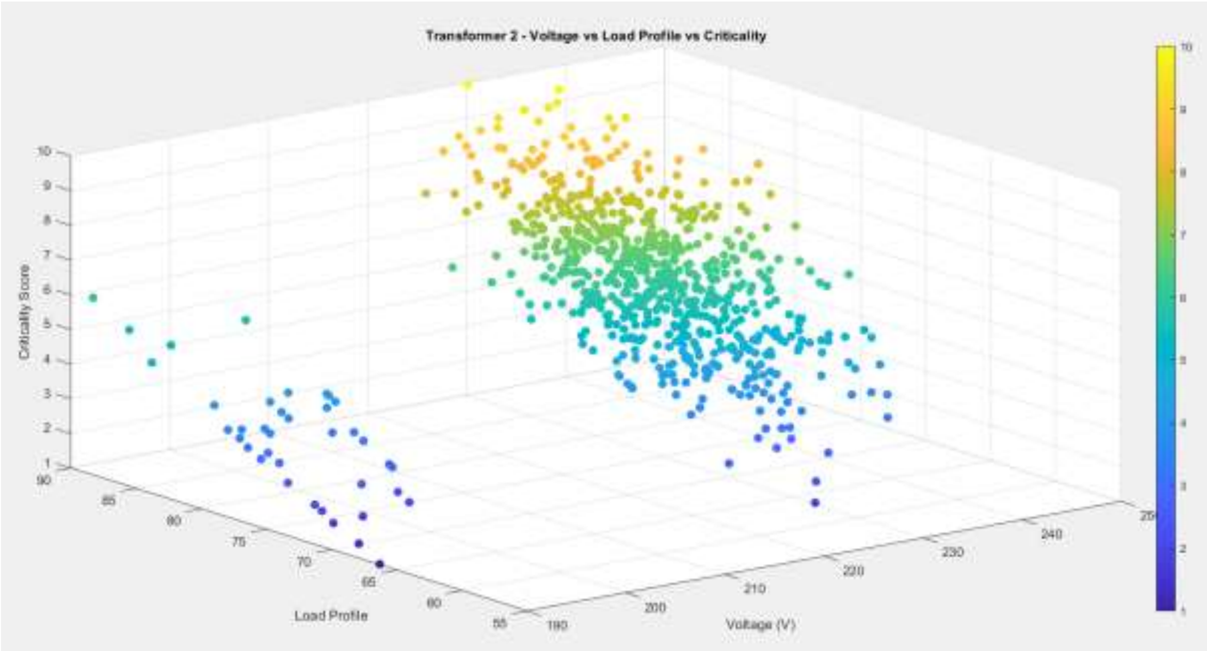

Figure 12. 3-D scatter plot illustrating the relationship between voltage, load profile, and criticality score based on the simulated datasets for transformer 2

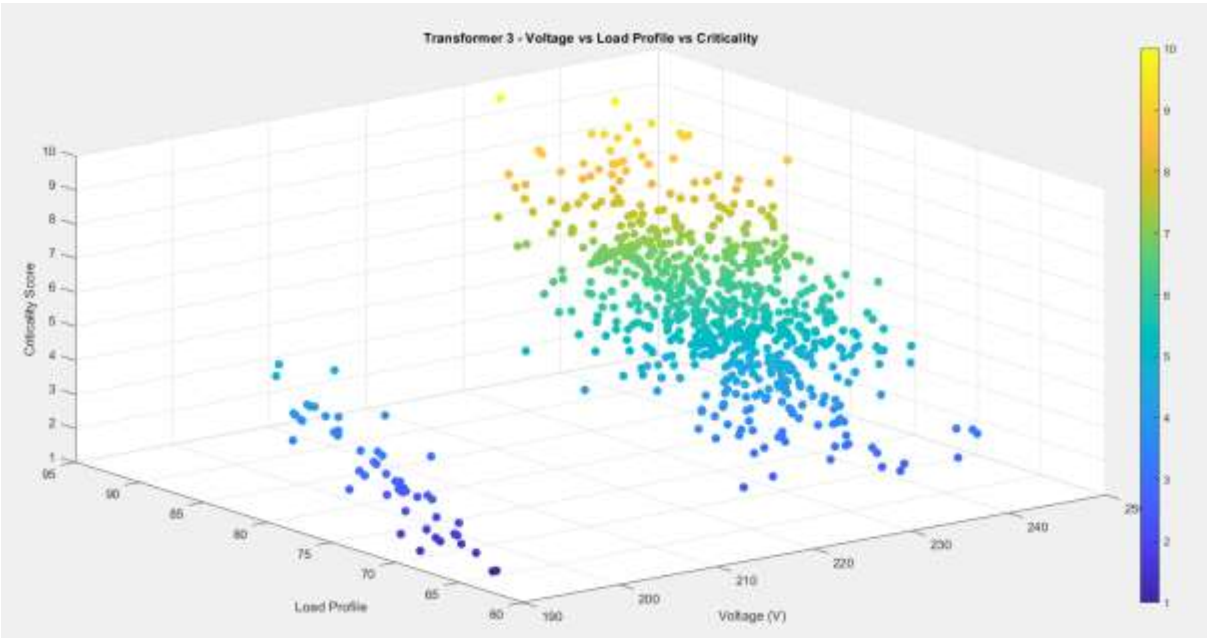

Figure 13. 3-D scatter plot illustrating the relationship between voltage, load profile, and criticality score based on the simulated datasets for transformer 3

With the completion of the data processing stage, predictive modeling was conducted to estimate transformer health status using historical and live/real-time (simulated) operational parameters.

A Regression Bagged Ensemble model was selected for predictive modeling, implemented using MATLAB 2024a – fitrensemble function [8]. This ensemble model, utilizing a Bootstrap Aggregating (Bagging) approach, was selected for its robustness against variance and its ability to handle fluctuations common in transformer sensor data. Specifically, multiple decision trees were trained and combined to provide stable and accurate predictions of the transformer Health Index [9].

The training features included key operational parameters: Voltage, Current, Active Power, Reactive Power, Apparent Power, Power Factor, Frequency, Energy Consumption, Load Profile, Ambient Temperature, Winding Temperature, and Oil Temperature. The target variable for prediction was the HI, as calculated in the data processing step, reflecting transformer health status based on deviations from nominal thermal conditions.

The datasets were split into 80% for model training and 20% for model testing, ensuring a rigorous and unbiased assessment. For Transformer 2, the predictive model achieved an RMSE of approximately 0.05, demonstrating high accuracy in estimating transformer health. Similarly, Transformer 3 achieved the same RMSE, indicating consistent model performance across different datasets.

The results for the two transformer datasets under study are presented in Figure 14 and Figure 15, presenting a comparison between actual and predicted Health Index values through scatter plots. These plots confirmed a strong correlation between actual and predicted values, with minimal deviations from the ideal reference line.

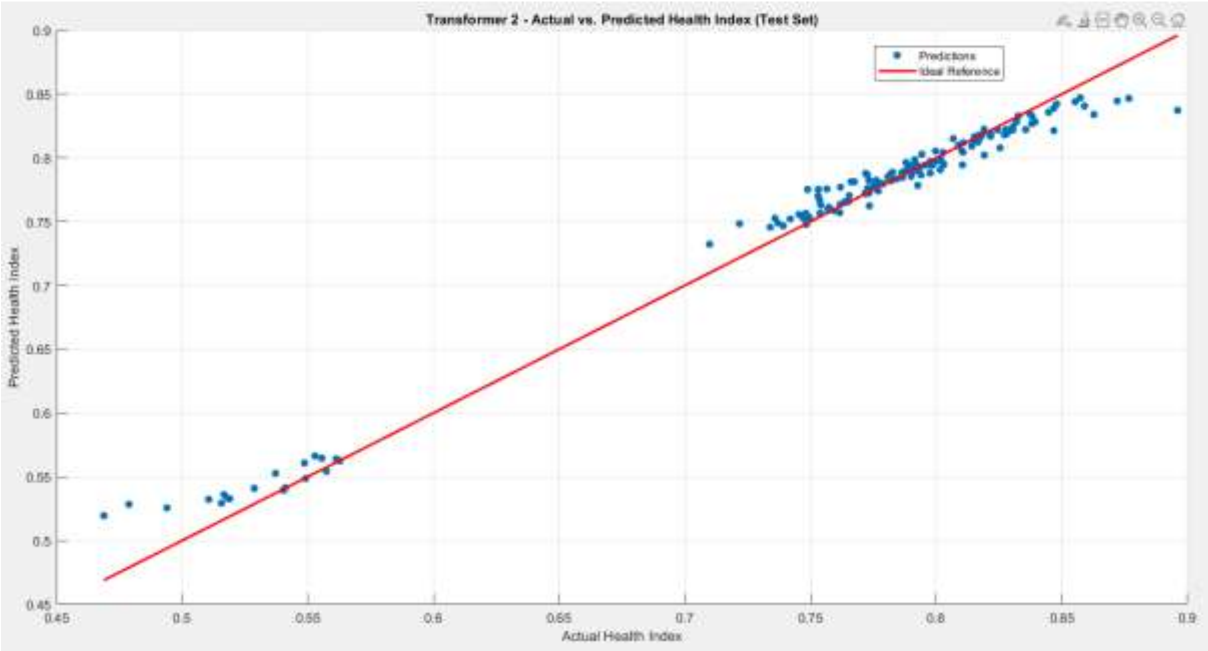

Figure 14. Comparison between actual and predicted Health Index after the training of the predictive model for the simulated datasets for transformer 2

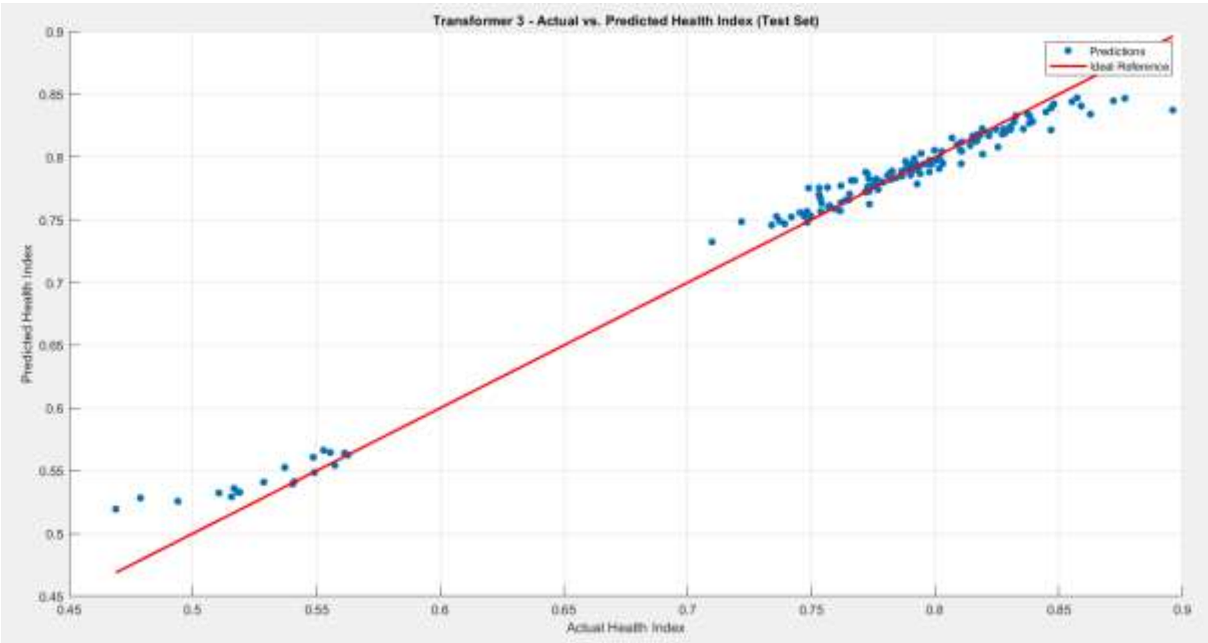

Figure 15. Comparison between actual and predicted *Health Index* after the training of the predictive model for the simulated datasets for transformer 3

After the predictive model is now trained, the next step is Anomaly Detection, where it is evaluated whether the model's predictions deviate from expected trends and detect abnormal behavior in transformer operations. The analysis in this test-case focused on monitoring voltage stability, thermal stress in winding temperatures, and power quality issues related to THD. For this test, the voltage threshold was set at 207V, consistent with operational standards, while winding temperatures above 90°C and THD levels exceeding 7% were flagged as anomalies. The detection process revealed a significant number of abnormal events in both transformers, with each one recording 53 voltage anomalies, 87 temperature anomalies, and 44 THD anomalies. This resulted in a total of 184 identified anomalies per transformer, as depicted in Figure 16 and Figure 17.

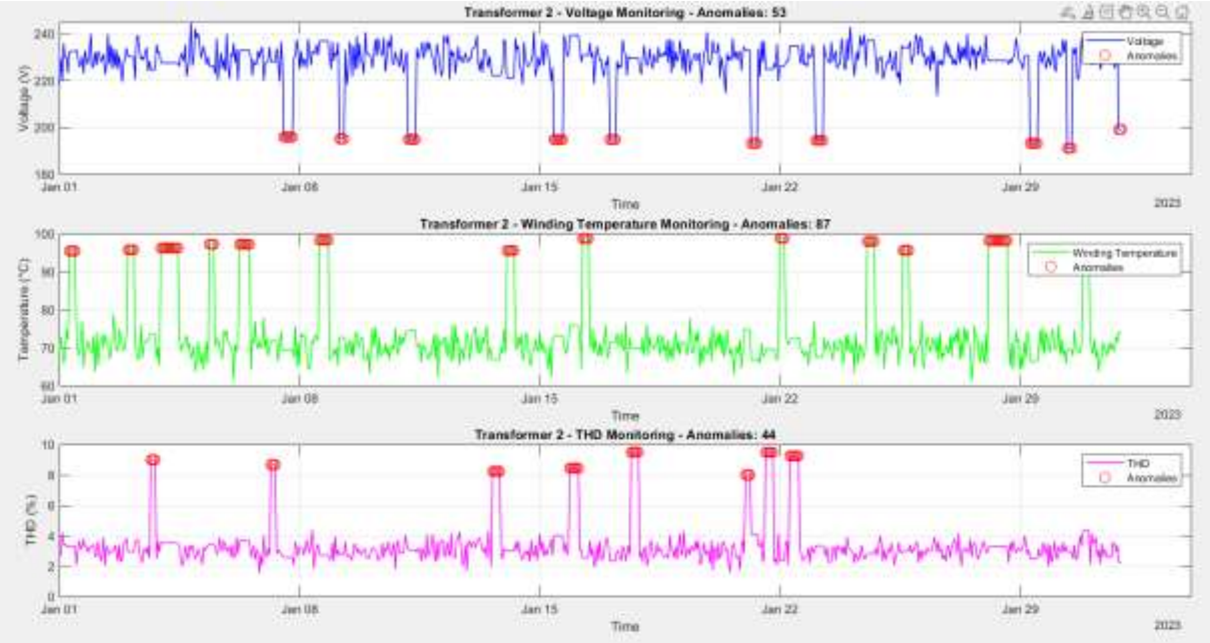

Figure 16. Identified anomalies based on the simulated datasets for transformer 2

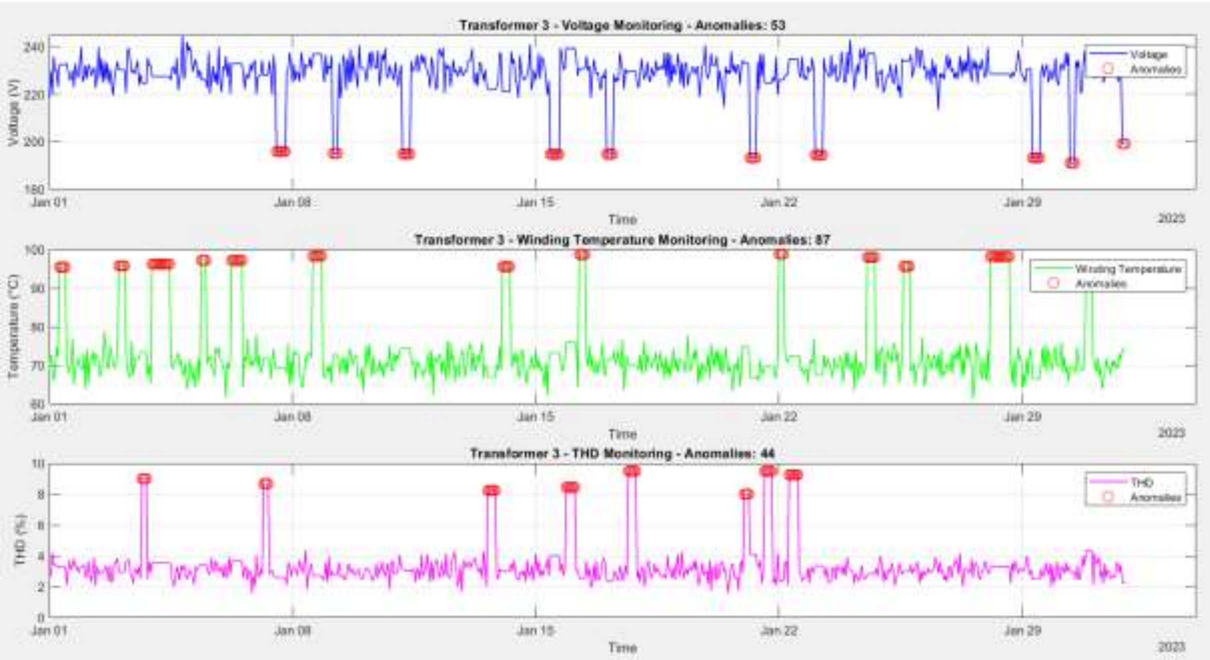

Figure 17. Identified anomalies based on the simulated datasets for transformer 3

The voltage anomalies indicate potential supply instability, which may be caused by excessive loading, fluctuations in distribution voltage, or network faults. Persistent voltage sags can lead to inefficient transformer performance and increased heating, which accelerates insulation degradation. The presence of 53 voltage-related anomalies suggests that further analysis is needed to assess the root causes of these fluctuations and their impact on long-term transformer reliability.

The winding temperature anomalies were the most frequent issue, with 87 recorded instances per transformer where temperatures exceeded the critical threshold of 90°C. Elevated thermal conditions accelerate the aging process of insulation materials, reducing the remaining useful life of the transformer. Persistent overheating can be attributed to high load conditions, insufficient cooling mechanisms, or external environmental factors such as elevated ambient temperatures. If left unaddressed, such conditions can lead to insulation breakdown and potential transformer failure.

THD anomalies were detected 44 times per transformer, signaling power quality concerns within the system. Excessive harmonic distortion negatively impacts transformer efficiency, contributing to additional heating and potential resonance issues. These anomalies suggest the presence of non-linear loads, such as industrial machinery or power electronic converters, that inject harmonics into the system. Elevated THD levels beyond 7% indicate the need for further investigation into load characteristics and potential mitigation strategies such as harmonic filters or improved network balancing.

The next step involves refining the prioritization of the detected anomalies (in this case the total of 184 detected anomalies) to focus on the most critical faults requiring intervention. The maintenance optimization phase classifies and schedules necessary corrective measures based on severity, ensuring that the most at-risk transformers receive timely attention to prevent failures and minimize operational disruptions.

The maintenance optimization process has been successfully completed for both Transformer 2 and Transformer 3. The optimization phase utilizes the detected anomalies, transformer health indicators, and feature correlations to prioritize and schedule maintenance tasks over a defined scheduling horizon. Figure 18 and

Figure 19 depict the heat maps illustrating the correlation between key transformer parameters, including voltage, winding temperature, THD, and load profile.

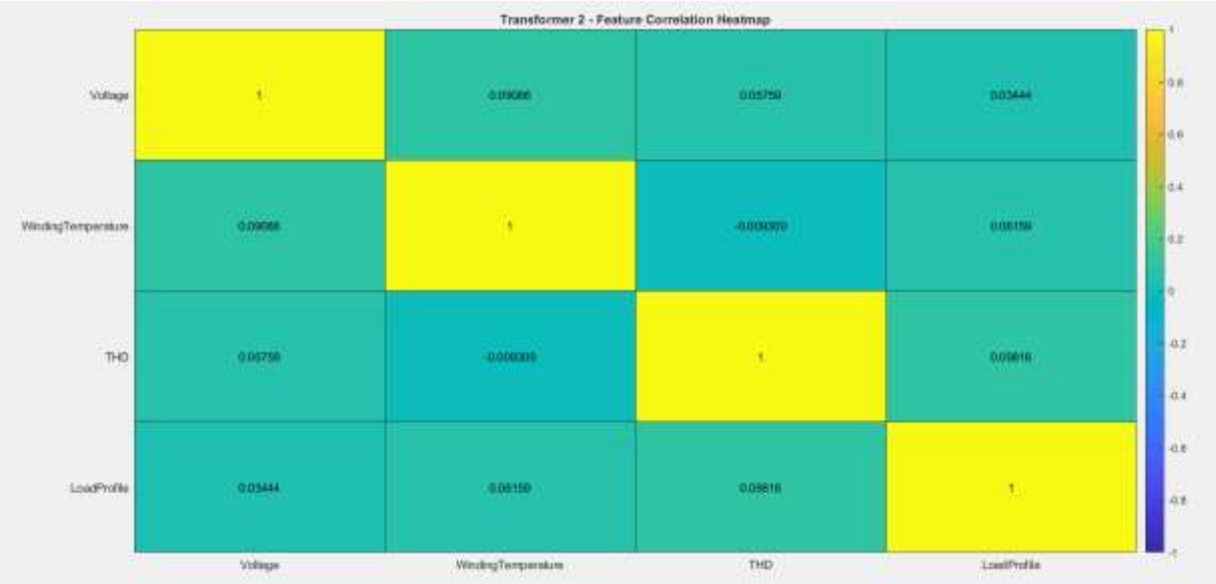

Figure 18. Correlation heat map for key transformer 2 parameters

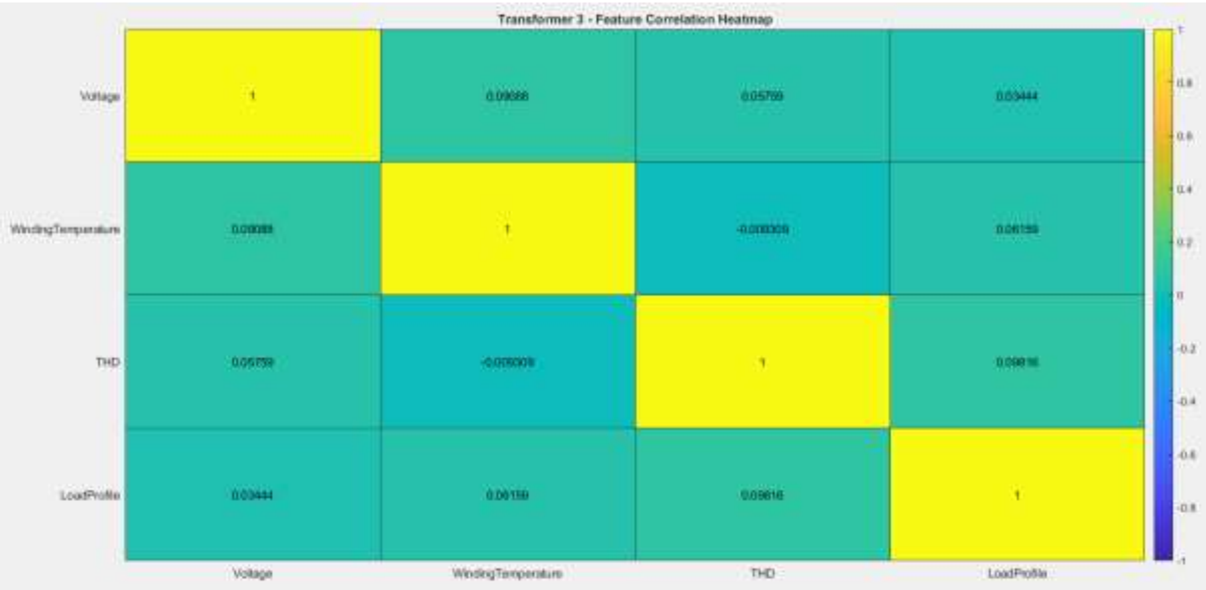

Figure 19. Correlation heat map for key transformer 3 parameters

The color scale in Figure 18 and Figure 19 ranges from -1 to 1, where values close to 1 indicate a strong positive correlation (i.e., when one parameter increases, the other also tends to increase), values near -1 represent strong negative correlations (i.e., when one parameter increases, the other tends to decrease), and values around 0 suggest weak or no correlation. These insights help in understanding which parameters contribute most to transformer degradation and guide maintenance prioritization based on critical feature interactions. The weak correlations also indicate that maintenance planning should rely on a combination of multiple condition indicators rather than a single dominant factor.

For Transformer 2, the heat map shows generally weak correlations among the features. The highest correlation observed is between voltage and winding temperature (0.0909), which suggests that voltage fluctuations have a slight impact on transformer heating. Similarly, THD and load profile exhibit a small correlation (0.0982), indicating that harmonic distortions may slightly increase with higher load levels. However, the overall low correlation values indicate that these features do not exhibit strong dependencies, suggesting that multiple independent factors influence transformer health and operational conditions.

The final output of this step is the proposed maintenance schedule for the transformers under study. Figure 20 presents the smart maintenance optimization schedule for Transformer 2, while Figure 21 illustrates the corresponding schedule for Transformer 3.

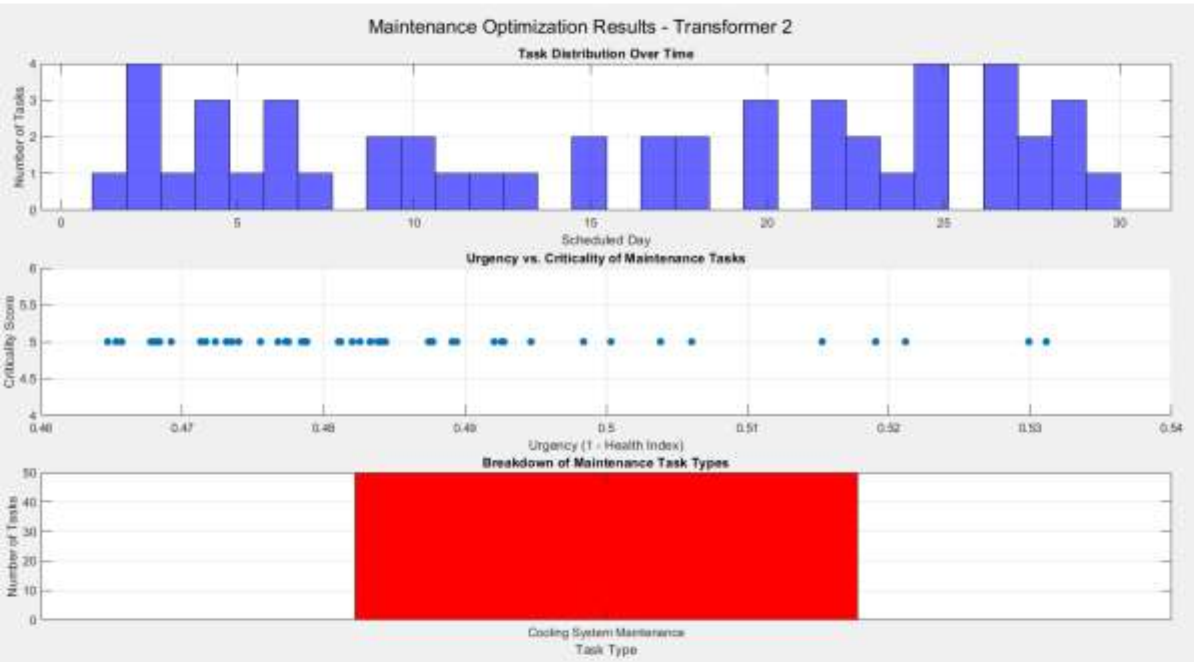

Figure 20. Smart Maintenance optimization schedule for transformer 2

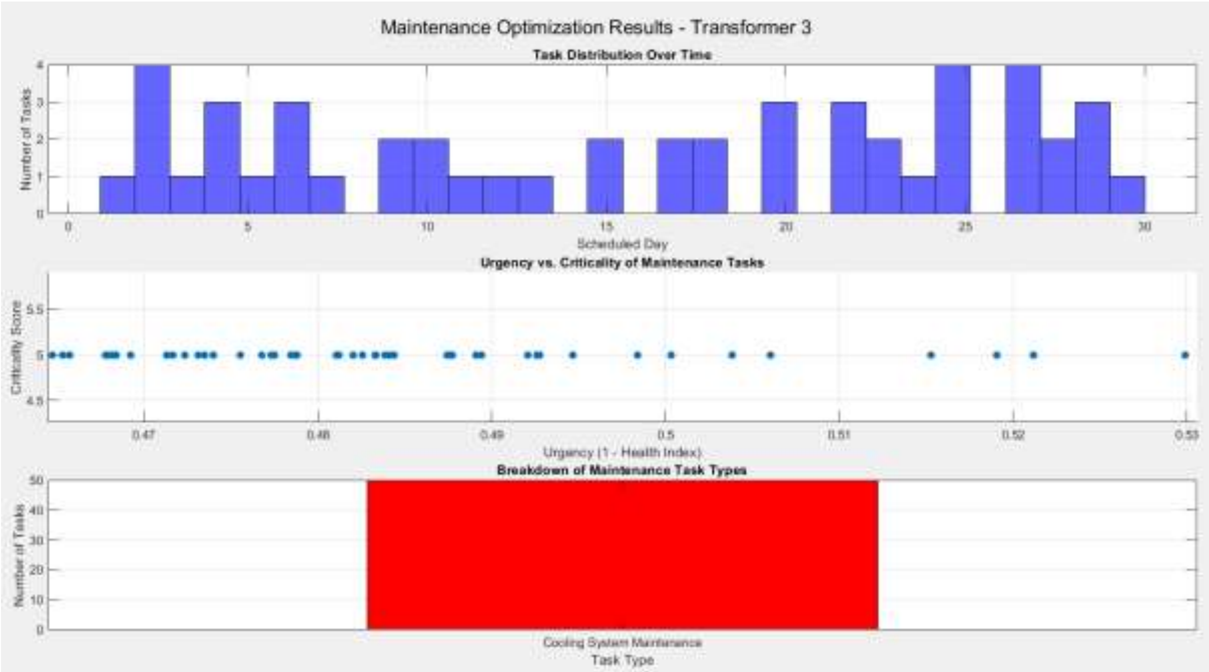

Figure 21. Smart Maintenance optimization schedule for transformer 3

For Transformer 2, the predictive maintenance tool identified and scheduled maintenance tasks within a 30-day optimization horizon. Tasks were prioritized based on asset-health evaluation combining transformer Health Index (HI), operational criticality, and correlation-weighted condition indicators (Voltage, Winding Temperature, THD, and Load Profile). A total of tasks was scheduled, predominantly classified as "Cooling System Maintenance," due to frequent winding temperature elevations beyond 95°C, indicating potential overheating risks.

Similarly, for Transformer 3, the predictive tool recommended an equivalent number of maintenance tasks. These tasks also predominantly classified as "Cooling System Maintenance" were systematically prioritized and scheduled according to their HI scores, with transformers exhibiting lower HI values (below 0.5) receiving higher urgency. The resulting schedule maintained a balanced distribution across the scheduling horizon, efficiently addressing transformers showing significant thermal stress indicators.

The validation visualizations highlight the effectiveness of integrating predictive health modeling (HI-based), feature weighting through correlation, and adherence to operational constraints. This combined approach ensures that the assets identified as most vulnerable to potential failures are proactively managed, thus enhancing system reliability and reducing unplanned outage risks.

The correlation analysis preceding the optimization revealed relatively weak direct correlations among the individual transformer operational parameters. Despite these low correlations, the current approach leveraging a HI-based predictive model combined with operational criticality effectively compensates for the limited linear correlation among individual parameters. The optimization algorithm successfully prioritizes maintenance tasks by incorporating nonlinear relationships captured by the predictive model, operational importance (criticality), and specific fault-type indicators (e.g., elevated winding temperature, THD). Consequently, even though direct correlation values among raw parameters might be limited, the integrated predictive modeling framework ensures accurate identification and proactive scheduling of critical maintenance tasks, aligning effectively with operational constraints and transformer health conditions.

2.2.2.4 Next Steps

The next steps should focus on implementation, validation, and integration of the Smart Grid Maintenance tool within the project's associated services and relevant pilot sites. The proposed action plan by the end of the task (i.e., M33) is the following:

- Finalization of the Computational Framework based on available mandatory grid asset's data and feedback from grid-level actors (especially DSOs/TSOs partners). Optimization models will be enhanced/modified to include grid constraints and operational flexibility.

- Streamline a structured data exchange via the EVELIXIA Services Broker that enables seamless data extraction from IS15-iVN, in parallel with the grid modelling progress, to incorporate continuous asset health monitoring and predictive simulations.

- Validation on Pilot Case Studies – The tool will be tested in the relevant project's pilot sites to validate its predictive accuracy and maintenance optimization strategies, provided that real mandatory data is available.

3 EVELIXIA'S AUTONOMOUS DISTRICT DECISION SUPPORT FRAMEWORK

The primary goal of network planning is to identify the most cost-effective investment strategy that meets the power transfer needs between energy sources and loads. Integrating renewable energy generation (REG), such as wind farms and solar power plants, into the grid often necessitates network investments while also accounting for environmental costs. Unlike conventional power plants, the operational characteristics of REG are highly variable and location-dependent, requiring adjustments or improvements to traditional network expansion methods.

Distribution network planning involves determining the optimal location and size of substations and feeders. Integrating distributed generation (DG), such as solar and wind, into the distribution network can reduce active power losses and delay the need for new infrastructure investments. However, increased penetration of REG can lead to challenges like line overloading and voltage regulation issues. Traditionally, these issues have been addressed by building new circuits to expand network capacity, but this approach is often time-intensive, costly, and may not always be feasible due to space or regulatory constraints. As wind and solar power depend heavily on geographic conditions, certain parts of the grid may experience congestion and require upgrades to accommodate more REG connections.

Modern approaches, such as active network management and advanced communication systems, can complement or replace traditional reinforcement strategies, offering solutions that are more flexible and cost-effective.

As REG connections continue to increase, certain areas of a distribution network may experience issues such as nodal (bus) voltage violations and line overloading. However, constructing new circuits to accommodate REG can entail significant financial and environmental cost.

Active network management schemes (such as enabling grid users' flexibility) constitute technical levers available to system operators as an alternative to grid reinforcement, to deal with the changing congestion issues and voltage challenges faced by the local grid due to the mass arrival of decentralized generation facilities.

Distribution automation can be treated as a supplementary scheme to traditional primary asset investments; network investments can be reduced or deferred by deploying active network management. If flexibility resources are available within the network operation, the identified capacity needs can be resolved or significantly reduced through the utilization of such flexible resources.

In light of this, the core objective of this task is to deliver tools that enable the identification of the minimum network investment scheme for the system operator satisfying the power transfer requirements from sources to loads, while also enabling the elimination of branches overloading by deploying active network management schemes.

Towards this objective, the simulation capabilities of the iVN under tasks T4.3 (see Section 2.2.1) will be leveraged to create a set of decision-making and support services at the district/grid level, including Grid Investment Planning services (IS11), Multi-vector Network Management services (IS12) and Aggregated Demand Portfolio Management services (IS13), as depicted in Figure 22. These services focus on grid stakeholders (grid operators – at the DSO level, also involving synergies with energy aggregators, retailers, etc.), providing services from the Grid to the Building (i.e., energy consumers) that could mutually benefit both sides.

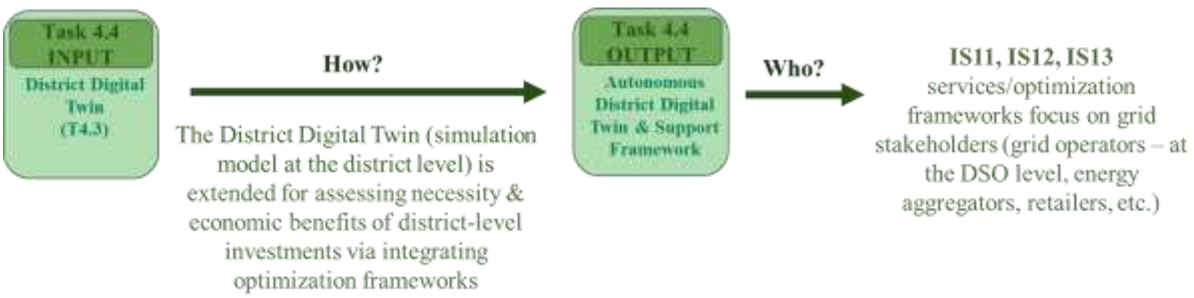

Figure 22. Linkage of T4.3 and T4.4 towards EVELIXIA Autonomous District Digital Twin & Support Framework

In Section 3, the key developments of Task 4.4 activities (Figure 23) are described, along with some preliminary results to showcase the functionalities of the tools (described in detail in Section 3.2).

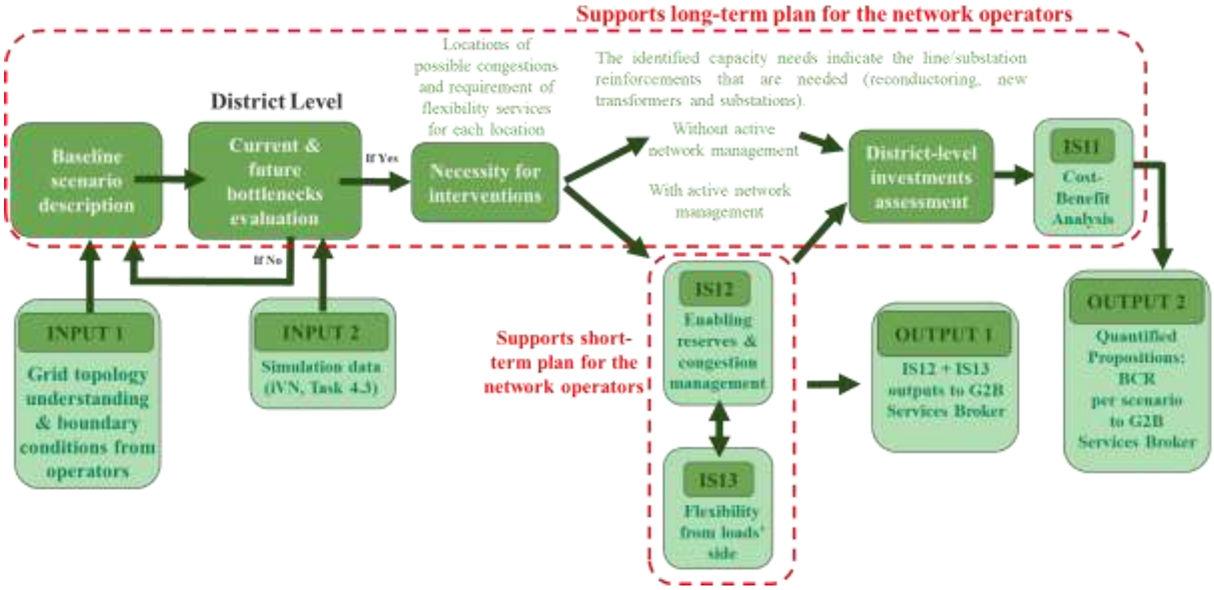

Figure 23. Methodology of T4.4 EVELIXIA services implementation. Inputs/Outputs are referred to T4.4

3.1 Introduction

Multivector energy systems refer to integrated energy systems that utilize various energy carriers—such as electricity, heat, hydrogen, and biofuels—interconnected within a single framework. These systems aim to optimize energy production, storage, and consumption by efficiently coordinating different forms of energy to enhance overall performance, reliability, and sustainability. Simulation and optimization of multivector energy systems requires sophisticated techno–economic tools that are capable of modelling buildings and distributed energy resources (DERs) across multivector energy networks. Towards this, the IS15 – iVN multi-vector grids energy modelling capabilities (see Section 2.2.1) will be leveraged for the enhancement of the Innovative Solutions developed under Task 4.4 activities, thus enabling automated decision-making for holistic system planning, operation, and maintenance across buildings and grid levels. Given that at this phase of the project the multi-vector grids modelling in Task 4.3 is under development, the focus of the ISs under Task 4.4 (Section 3) is shifted towards the flexibility of the electricity distribution grid (mainly focusing on local congestion management via distribution grid related services) without compromising the increasing interdependence among the different energy vectors at the distribution level (i.e., electricity, district heating, and natural gas systems). Thus, the proposed framework (Figure 23) enables the synergy of the different system operators, which is not the case in the current state of the deregulated energy commodities market[4].

3.2 Autonomous District Digital Twin – Solution Design Overview

Task 4.4 aims to create develop and implement three discrete yet cooperative Innovative Solutions (ISs):

- Grid Investment Planning Assistant Service (IS11): Supporting long-term system planning for local grid operators' (e.g., DSOs) based on proactive identification of future bottlenecks, assessing the necessity of potential interventions and evaluating in terms of economic benefit (direct investment profits from network enhancements) and economic viability. Performs a Cost-Benefit Analysis (CBA) to compare different grid investment scenarios.
- Multi-Vector Energy Network Manager Service (IS12): Targeting grid operators (e.g., DSOs), enables services at the grid level (focusing on local congestion management via flexibility-based solutions), without violating operational bounds of the different energy networks.
- Aggregated Demand Portfolio Manager Service (IS13): Targeting Aggregators applies real-time daily portfolio replanning/rescheduling at an aggregated building and district scale, to enable proactive resources (demand flexibility) aggregation and allow active participation in energy balancing markets (focusing on the electricity vector).

These ISs are presented in detail in the following subsections.

3.2.1 Grid Investment Planning Assistant (IS11)

The Grid Investment Planning Assistant (GIPA) is a decision-support tool designed to evaluate current and future network bottlenecks and assess the economic viability of potential grid infrastructure upgrades. It provides a structured and quantitative approach for investment planning at the grid level, incorporating a

[4] The heating market is far less competitive and mature than the power and natural gas market, and the market clear cycles of electricity and natural gas markets are different.

detailed CBA based on the ENTSO-E CBA guidelines to compare different strategies such as network reinforcement, active network management, and DER integration.

The tool supports DSOs and policymakers in making informed, cost-effective, and sustainable investment decisions, by considering technical constraints, other constraints (such as geographic limitations, regulatory requirements), and socio-economic factors. It enables comprehensive economic feasibility evaluations of different grid reinforcement strategies, including traditional upgrades (e.g., new line installations, substation expansion, transformer replacement) and smart grid solutions (e.g., SCADA upgrades, demand response mechanisms, grid-scale energy storage).

GIPA extracts the necessary input data from the Multi-Vector Grids Energy Modelling & Simulation solution (IS15), vector congestion forecasting, and capacity building analysis from RES and storage integration, i.e., assessment of the energy system's ability to accommodate and optimize the integration of RES and storage technologies over time.

The tool incorporates technical, economic, and environmental dimensions to assess the long-term projected district-level scenarios, to ensure that multi-grid modernization strategies meet the challenges of increasing electricity demand, renewable penetration, and grid reliability while maximizing economic benefits and ensuring efficient allocation of resources via various grid upgrade scenarios.

3.2.1.1 Objectives

IS11 - Technical Objective "TRL5 to TRL7": Originally validated in the relevant environment of several past EU-funded projects (e.g. IANOS GA No. 957810) GIPA is introduced to EVELIXIA at Technology Readiness Level (TRL) 5. Advancing towards TRL6, a working version of IS11 is tested in a simplified, small-scale network based on the IEEE 33 bus radial distribution system, as it is further described in Section 3.2.1.3. The final version of the GIPA will undergo validation using simulation data generated by IS15 - intelligent Virtual Network – iVN (Section 2.2.1), ensuring applicability to each pilot site network under study. As part of EVELIXIA's platform integration, progressing towards TRL 7 until the end of the project, future efforts and refinements of the tool target demonstration of the technology across

EVELIXIA pilot sites, thus ensuring its applicability in real-world grid investment planning and decision-making.

IS11 - Scientific Objective: Economic valuation & monetization of grid investment scenarios. GIPA enables the quantification and monetization of investment benefits across EVELIXIA's pilot sites, providing economic assessment indicators (i.e., Net Present Value (NPV) and Benefit-Cost Ratio (BCR)). GIPA employs a multi-layered methodology that identifies grid-level investments that maximize economic, environmental, and by extension, social value (Section 3.2.1.2).

3.2.1.2 Methodology

GIPA follows a structured methodology for evaluating grid investment scenarios by integrating CBA principles based on the ENTSO-E CBA guidelines [10], [11]. The process ensures a comprehensive evaluation of grid upgrade options, monetization of benefits, and cost assessments to determine the most viable investment pathway.

Tailoring the workflow to the needs of EVELIXIA (Figure 24) the methodological approach breaks down into two core features, the Scenario Analysis and the CBA. The evaluation of existing/future bottlenecks derives as the output of the simulation engine (i.e., EVELIXIA district DT) and contributes to assessing the necessity for infrastructure interventions/investments (network-specific KPIs that will serve the benefit monetizing phase of the CBA), providing the required inputs from the end-user (i.e., the targeted users, e.g., the grid under study operations), via the EVELIXIA platform. The methodology further employs:

- Multi-Criteria Investment Assessment, in the sense that upgrade investments are evaluated based on multiple KPIs, reflecting technical performance and environmental indicators towards socio-economic welfare Thus, the tool provides a structured decision-making process for network expansion and optimization.
- DER Grid Integration, assessing the economic feasibility of integrating variable RES and storage as cost-effective solutions to mitigate challenges such as congestion, curtailment, and voltage violations.
- Scenario-Based Grid Planning, enabling the comparison of different investment strategies by simulating multiple grid upgrade scenarios.

- Environmental and Social Impact Considerations, incorporating carbon footprint reduction, grid resilience improvements, and social benefits (e.g., improved service reliability), which aligns with EU regulatory frameworks and climate goals for sustainable energy infrastructure.
- Uncertainty Planning, via parametric analysis to assess investment risks under varying future conditions, such as changing energy prices, policy shifts and regulatory changes, demand growth and peak load variations, renewable energy penetration levels).

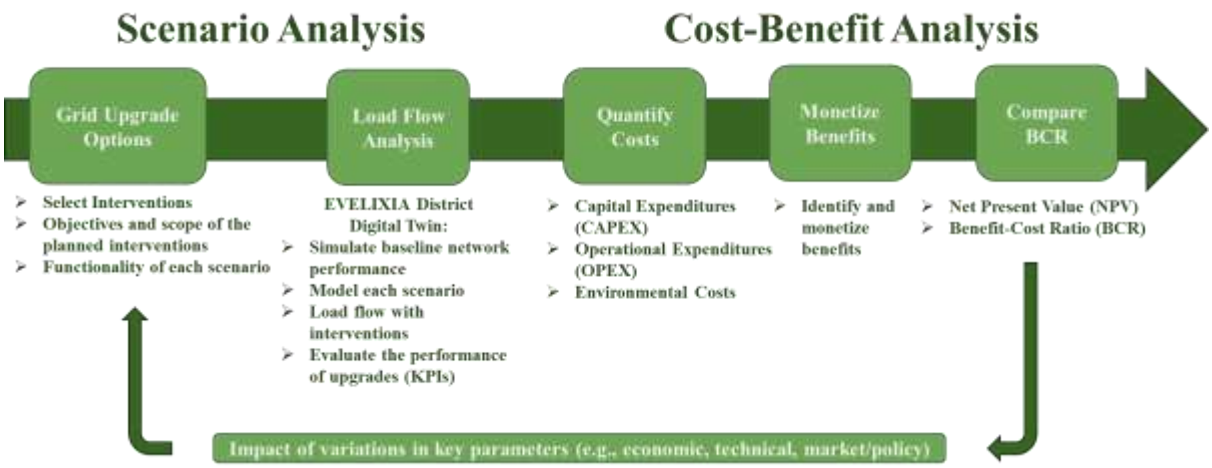

Figure 24. Grid Investment Planning Assistant (GIPA) workflow

Scenario Analysis

The grid upgrade options (Figure 24) are defined based on projected estimates of system needs, identifying necessary interventions to support renewable energy integration, congestion management, and grid flexibility enhancement. Various upgrade options relevant for the EVELIXIA scope and objectives are to be considered, aligned with system operators' best practices, including but may not limited to advanced SCADA and control system upgrades, new substations and grid reinforcements, grid-scale BESS, and reconductoring or capacity expansion of existing lines. Each upgrade scenario is assessed based on its technical and operational role, evaluating how interventions contribute to improving grid flexibility, stability, and resilience. This assessment involves mapping elements and assets to specific functionalities, (e.g., congestion mitigation), while also translating these functionalities into quantifiable benefits. These benefits are categorized into economic aspects, including cost savings and deferred investments in grid reinforcement, environmental improvements, such as CO_2 emissions reduction and better renewable energy utilization, and operational enhancements, including voltage stability, reduced congestion, and improved system reliability.

The load flow analysis (Figure 24) serves as a critical step in evaluating the baseline network conditions and the impact of proposed grid upgrades. In the EVELIXIA framework, this analysis is conducted through the District Digital Twin, implemented within IS15-iVN, which enables a detailed assessment of grid performance under current and projected conditions. The baseline simulation provides insights into existing grid constraints, voltage deviations, and risks of network overloading, particularly under anticipated demand growth and increasing renewable energy penetration.

Following this, the selected upgrade scenarios (relevant for each application case within the EVELIXIA, according to the involved stakeholders' feedback) are integrated into the simulation model to analyse their effectiveness in addressing the observed bottlenecks. By running power flow simulations under different intervention strategies, the model quantifies the improvements in grid stability, congestion relief, and renewable hosting capacity.

To systematically evaluate the benefits of each upgrade scenario, a set of Key Performance Indicators (KPIs) is defined, measuring key aspects of grid operation. These indicators provide a quantitative basis for comparing different grid upgrade strategies. **Table 1** summarizes a provisional KPIs list related to grid operation and performance and their respective calculation formulas [12], [13]. This KPI list will be updated upon integration of the EVELIXIA platform and refined according to the site-specific needs of respective grid-level actors. The final KPIs will be based on calculations performed in the simulation engine, based on the grid-level stakeholders input data and feedback.

Table 1. Provisional KPIs list related to grid operation and performance and their respective calculation formulas

KPI	Description	Formula	Unit
Energy Curtailment Reduction	Reduction in curtailed energy due to grid investment or flexibility solutions.	$\Delta C = E_{curt,base} - E_{cur,investment}$ $E_{curt,base}$ = Total curtailed energy under the baseline scenario (MWh/year). $E_{curt,investment}$ = Total curtailed energy after grid investment (MWh/year).	MWh/year
Energy Loss Reduction	Reduction in transmission and distribution losses due to grid reinforcement.	$\Delta E = E_{loss,base} - E_{loss,investment}$ $E_{loss,base}$ = Total annual energy losses under the baseline scenario (MWh/year). $E_{loss,investment}$ = Total annual energy losses after grid investment (MWh/year).	MWh/year
System Load Factor Improvement	Improvement in the ratio of average to peak load, indicating better grid utilization.	$LF = \frac{\text{Average Load}}{\text{Peak Load}} x\ 100\%$ LF : load factor (%). *Average Load*: mean power demand over a given period (MW). *Peak Load*: maximum power demand observed in that period (MW). $LF\ Improvment = \frac{LF_{investment} - LF_{base}}{LF_{base}} x\ 100\%$ $LF_{investment}$: Load Factor after grid upgrade or flexibility intervention. LF_{base}: Load Factor under the baseline scenario.	%
CO_2 Emissions Avoided	Reduction in emissions due to increased renewable integration and reduced fossil-	$CO_2\ Avoided = \sum [E_{RES,used} x (\frac{F_{fossil}}{F_{total}}) x\ EF_{grid}]$ $E_{RES,used}$: additional renewable energy utilized due to the intervention (MWh).	tons CO_2/year

	based generation.	F_{fossil}: amount of fossil fuel-based electricity generation (in MWh). F_{total}: total electricity generated in the grid (in MWh). EF_{grid}: average CO_2 emission factor of the grid (in tons CO_2/MWh).	
Grid Congestion Relief (Percentage Reduction)	Reduction in congestion levels on network assets (e.g., transformers, lines) after implementing a flexibility or reinforcement measure.	$\frac{\lvert H_{base}\rvert - \lvert H_{investment}\rvert}{\lvert H_{base}\rvert} \times 100\%$ H_{base}: hours per year when network elements exceed a predefined congestion threshold (e.g., 80%-line loading) before intervention. $H_{investment}$: hours per year when network elements exceed the threshold after intervention.	%
Voltage Stability Improvement	Reduction in voltage deviations from nominal levels at key network nodes.	$\frac{\lvert V_{base}\rvert - \lvert V_{investment}\rvert}{\lvert V_{base}\rvert} \times 100\%$ V_{base}: maximum voltage deviation before intervention (pu). $V_{investment}$: maximum voltage deviation after intervention (pu).	%

Cost-Benefit Analysis

The objective of the CBA process is to quantify the costs and benefits associated with a proposed intervention in measurable terms, ensuring that investment decisions are financially sound. The analysis includes both direct financial impacts and monetized values of non-monetary benefits such as environmental improvements and system reliability.

The first step involves defining the cost components. Once the baseline and intervention cases are established, the cost quantification incorporates Capital Expenditure (CAPEX)—covering infrastructure deployment, grid expansion, RES and storage investments—as well as Operational Expenditure (OPEX) for maintenance and monitoring. Additionally, Environmental Costs related to emissions or sustainability concerns are factored in.

The expected benefits are monetized to reflect their economic value. This includes for example converting deferred transformer or substation expansion into avoided network upgrade costs, lower energy losses into reduced operational expenditure, congestion management into avoided curtailment costs, etc. Similarly, enhanced system reliability is translated into avoided downtime costs, while reduced CO_2 emissions and improved energy efficiency are monetized using standardized carbon pricing metrics (such as €/ton of CO_2 avoided), derived from carbon taxation schemes or emissions trading systems (ETS). At this stage, the analysis also identifies the key beneficiaries, which may include TSOs, DSOs, consumers, policymakers, and renewable energy investors.

The financial viability of the investment is then determined through standard economic performance metrics. The Net Present Value (NPV) is computed by summing the discounted monetary benefits and subtracting the discounted costs over the project's lifetime, with a positive NPV indicating a financially attractive investment. The Benefit-Cost Ratio (BCR) is calculated by dividing the total present value of benefits by the total present value of costs, with a BCR greater than one signifying a viable and justifiable investment [11].

To account for uncertainties and risks, GIPA incorporates will evaluate the impact of the variation in key parameters from the scenario analysis for grid upgrades stage (Figure 24) that serves as input to the CBA, assessing the robustness of investment decisions under varying conditions, including but not limited to the impact of demand growth variations (which affect electricity consumption and grid constraints), market price fluctuations (which influence investment profitability), and renewable energy penetration (which alters the need for flexibility solutions). Furthermore, regulatory and policy changes—such as new incentive mechanisms, evolving market rules, or adjustments in CO_2 pricing—should be also considered to enhance decision-making resilience and adaptability to future grid conditions.

CBA Formulation – Parameters and Definitions

The static/dynamic input data in the formulation that follows are provided requested by the interested users of GIPA and extracted from IS15-iVN.

Net Present Value (NPV): The NPV is the monetary amount of the change in the value of the energy infrastructure due to selecting and applying one or more interventions according to the business objectives set by the involved stakeholders. A positive NPV suggests a profitable investment. The NPV is calculated by summing the present values of all benefits and subtracting the present values of all costs:

$$NPV = \sum_{t=1}^{T} \frac{(B_t - C_{op,t} - C_{env,t})}{(1+r)^t} - C_{env,embodied} - C_{env,EoL} - C_{inv} \qquad \text{Eq. 3.2.1.1}$$

where:

B_t: Benefits in year t, resulting from energy savings, reliability improvements, demand response optimization, and other grid-related enhancements:

$$B_t = B_{energy,t} + B_{reliability,t} + B_{DR,t} + B_{curtailment,t} + B_{other,t} \qquad \text{Eq. 3.2.1.2}$$

where $B_{energy,t}$ can be expresses as *the sum of*

Grid Losses Avoided$_t$[5] ×*Electricity Price*$_t$[6] *and any Generated Revenue*$_t$[7], $B_{reliability,t}$[8] can be calculated as the sum of *SAIDI*[9] *Reduction*$_t$×*VoLL*[10] and *SAIFI*[11] *Reduction*$_t$ × *Outage Cost per Event*[12], $B_{DR,t}$ *(where relevant for involved stakeholders in the study) can be calculated via the sum of Peak Demand Reduction*$_t$[13] ×*Capacity Market Price*[14] and *DSO/ TSO Flexibility Payment*$_t$[15], $B_{curtailment,t}$ term

[5] *Grid Losses Avoided* account for reduction in MWh of energy losses due to grid efficiency improvements.
[6] *Electricity Price* is the cost of energy per MWh (e.g., wholesale market price).
[7] This term is applicable in cases of generated revenue streams, e.g., any revenue from charging/discharging storage via arbitrage mechanism at different price periods.
[8] This term refers to the case that grid investments directly reduce outage frequency; alternatively, this applies only to flexibility solutions.
[9] *SAIDI* is the System Average Interruption Duration Index (in hours).
[10] *VoLL* is the Value of Lost Load, i.e., the economic loss per MWh of unserved energy (€/MWh).
[11] *SAIFI* is the System Average Interruption Frequency Index.
[12] Economic impact per outage event (€).
[13] Reduction in MW of peak demand.
[14] Payment per MW of capacity reduction.
[15] Compensation from DSO/TSO for DR services.

coresponds to *Avoided Curtailment*$_t$×*Market Price of RES*$_t$ and finally $B_{other,t}$ refers to *Other Market Revenues* (e.g., CO_2 credits – i.e., revenue from carbon trading, ancillary services revenue – payment from TSOs for grid support, voltage regulation benefit – economic savings from better voltage stability, and other).

In Eq. 3.2.1.2, it should be noted that the benefits can vary by scenario (e.g., BESS might contribute more to arbitrage, while a new transformer mainly reduces curtailment and reliability costs, etc.). Also, some benefits (e.g., avoided curtailment) may increase over time with RES penetration, while B_t (when used in NPV) is discounted over time. Finally, the Eq. 3.2.1.2 formula is expressed in its most general form, making it universally applicable to all relevant scenarios; this depends on the specific interventions, their impact and the beneficiaries (stakeholders) – e.g., third-party BESS aggregators might receive ancillary payments, but DSOs might not). Thus, for practical studies, each benefit source is matched to the stakeholder who receives it. However, they are included in this part for the completion of the analysis.

$C_{op,t}$: Operational Expenditure (OPEX) in year *t*, including expenses incurred to maintain the investment over time. Represents yearly operational and maintenance costs (e.g., BESS degradation, transformer maintenance, SCADA system upkeep, and grid monitoring).

$C_{env,t}$: Environmental costs in a year t due to operational emissions and energy losses.

$$C_{env,t} = CO_2\ cost\ x\ CO_2\ emissions_t + Energy\text{-}Losses_t\ x\ Energy\ Cost \qquad \text{Eq. 3.2.1.3}$$

where

- *CO_2 cost*: the static price of CO_2 emissions per ton (€/ton), as set by carbon markets (EU ETS) or regulatory frameworks
- *CO_2 emissions*$_t$: the annual operational carbon emissions in year *t* (ton_{eq})
- *Energy Losses*$_t$: the energy losses associated with increased transmission and distribution losses (MWh) due to inefficient power flows
- *Energy Cost*: the static market price of imported or exported electricity depending on the scenario (€/MWh)

$C_{env,embodied}$: Environmental costs due to embodied energy and emissions

$$C_{env,embodied} = \ CO_2\ embodied\ x\ CO_2\ cost\ + PED\ embodied\ x\ Energy\ Cost$$

Eq. 3.2.1.4

- *CO_2 embodied:* the emissions embodied in component *j* (ton_{eq}) associated with the manufacturing, transportation and installation of the component (Stage A of its lifetime)
- *PED embodied: the embodied energy (MWh) during the production, transportation, and installation of components (Stage A of its lifecycle)*

$C_{env,EoL}$: Environmental costs due to End-of-Life energy and emissions

$$C_{env,EoL} = \ {CO_2}_{EoL}\ x\ CO_2\ cost\ +\ PED_{EoL}\ x\ Energy\ Cost \qquad \text{Eq. 3.2.1.5}$$

- *CO_{2EoL}: the emissions generated during the disposal treatment, and final fate of a product at the end of its useful life*
- *PED_{EoL}*: the primary energy (MWh) required for the disposal, treatment, and final fate of a product at the end of its useful life.

In case of lack of input data for the calculation of the $C_{env,embodied}$ (Eq. 3.2.1.4) and the $C_{env,EoL}$ (Eq. 3.2.1.5) of district-level energy carriers (generators, storage, power plants, charging stations, transformers) (e.g., aggregators, operators, manufacturers) key static information will be sourced from the Lifecycle Inventory (LCI) provided by CERTH/CPERI.

C_{inv}: Initial investment costs, i.e. CApital Expenditure (CAPEX), including infrastructure upgrades (e.g., BESS deployment, reconductoring, SCADA, new substations, etc.). Investment costs include all the upfront expenditure required to implement the grid intervention:

$$C_{inv} = \sum_{i=1}^{N}(C_{equip,i} + \ C_{install,i}) \qquad \text{Eq. 3.2.1.6}$$

where $C_{equip,i}$ is the equipment cost for asset *i* (e.g., BESS, transformer, etc.), $C_{install,i}$ is the installation and commissioning cost of asset *i*, and *N* is the total number of grid assets in the investment.

r: Discount rate applied to future costs and benefits. The discount rate reflects the time value of money and investment risk, typically based on the project's cost of capital, risk profile, inflation, market conditions, and industry standards. In energy projects, regulated entities use lower rates (3%-7%) for societal benefits [14], while private investors apply higher rates (8%-12%) to meet return expectations [15].

t: The project's time horizon, typically in the range of a 10-, 20- or 30-years horizon. It is important to note that the duration in years is defined by the interested stakeholder/site operator/aggregator etc. for each set of scenarios.

Benefit-Cost Ratio (BCR): The BCR is the ratio of the present value of benefits to the present value of costs. A BCR greater than 1 indicates an economically viable investment (as already mentioned), meaning the benefits outweigh the costs. BCR is computed by dividing the total present value of benefits by the total present value of costs:

$$BCR = \frac{\sum_{t=1}^{T}\frac{B_t}{(1+r)^t}}{C_{inv} + C_{env,embodied} + C_{env,EoL} + \sum_{t=1}^{T}\frac{C_{op,t}+C_{env,t}}{(1+r)^t}} \qquad \text{Eq. 3.2.1.7}$$

where the numerator accounts for the present value of all benefits over the project lifetime, while the denominator is the sum of the initial investment, the present value of operational and associated environmental costs over the project lifetime.

3.2.1.3 Evaluation & Results

Given that at the current stage of the project the grid modeling is under development, a preliminary test-run is set up in an alternative software environment to validate the tool's functionality and performance. Specifically, the GIPA methodology is initially tested in a modified, small-scale IEEE 33-bus test system [16] developed in MATLAB R2024a, reduced to a 5-bus network (test system) that represents a simplified distribution network operated at the DSO level, to evaluate investment decisions in grid reinforcement and congestion management. This test-run serves as a validation of the methodology, which aims to assess the cost-effectiveness of network upgrades while considering KPIs such as voltage stability, transformer loading, and grid losses. In addition, due to lack of a real-world case study at this phase, the applicability of the tool has been tested via simplified formulas, based on the methodology of Section 3.2.1.2. The power flow model was developed in MATPOWER v8.0 [17] ensuring accurate AC power flow calculations. Overall, this test-run is a means of verifying that the CBA methodology is successfully integrated with the Scenario Analysis and the power flow stages of the proposed workflow in Figure 24.

In this case study, a new grid line addition is evaluated against a Business-as-Usual (BaU) case, quantifying NPV and BCR under different discount rates and demand growth assumptions. The test system consists of five representative buses based on key grid characteristics: Bus 1 being the slack bus (primary substation), Load Bus 2 (e.g., medium-sized load center – 5 MW), Load Bus 3 (e.g., industrial or commercial load center – 8 MW), Load Bus 4 (e.g., residential or mixed-use load center – 3 MW) and Generation Bus 5: Renewable energy injection (e.g., distributed solar or wind, – 10 MW exports). Annex 1 (Section 6.1) includes the MATPOWER implementation of the modified IEEE 33-bus test system, adapted for the analysis.

The BaU case refers to the state of the grid under study when no new infrastructure investment is made, and the existing network continues to operate under its current conditions. Under this case, the grid experiences significant operational inefficiencies, including high transformer loading, increased voltage deviations, and considerable grid losses. These inefficiencies contribute to increased operational and environmental costs, primarily due to excessive energy losses and the associated carbon footprint.

The investment scenario under study, referred to as the New Line Addition, involves a targeted grid reinforcement measure in which a new transmission line is installed between Bus 3 and Bus 5. This intervention is expected to reduce congestion, enhance voltage stability, and lower transformer loading, thereby improving overall grid reliability.

Technical Performance Evaluation

To evaluate the effectiveness of this investment, after running the power flow simulations for both scenarios, the quantitative results are mapped into specific KPIs (based on **Table** 1). The new line addition resulted in a 40% reduction in voltage deviation, decreasing from 0.05 per unit (pu) in the BaU scenario to 0.03 pu, while the reinforcement led to a 23% decrease in transformer loading, lowering it from 98% to 75%, thus alleviating stress on network assets and improving the longevity of infrastructure components. Grid losses, a major source of inefficiency, were also significantly reduced. In the BaU case, annual grid losses amounted to 3.5 MWh, whereas the introduction of the new line reduced them to 1.8 MWh, marking an improvement of approximately 48.5%. These technical benefits are translated into economic savings, primarily through reduced operational and environmental costs. These results are depicted in Figure 25.

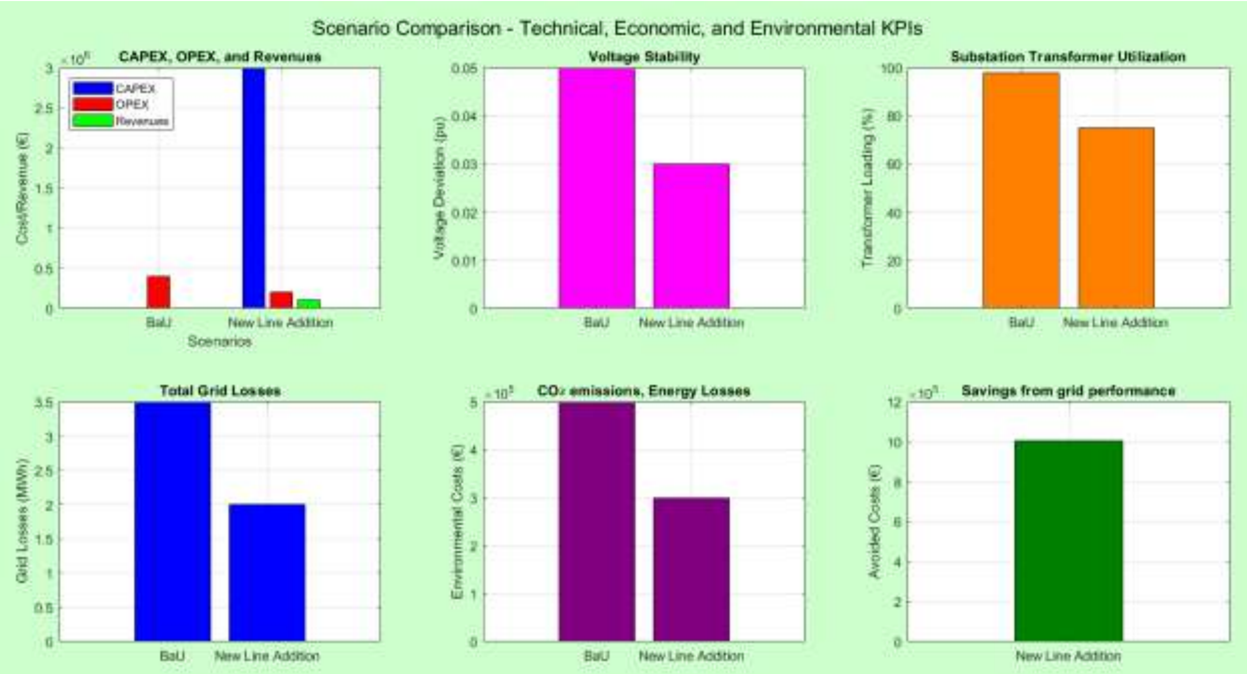

Figure 25. Power flow results for the 5-bus system under study: Technical and economical-environmental metrics

The evaluation of these scenarios for the test-run is based on real-world economic and environmental assumptions. The cost of implementing this reinforcement is estimated at €5 million, covering CAPEX related to equipment, installation, and commissioning. Additionally, OPEX for maintenance is assumed to be €300,000 per year, reflecting the costs associated with routine inspections and upkeep of the newly installed infrastructure [18]. Furthermore, the cost of energy losses was assumed to be €100 per MWh, a value derived from historical electricity market prices within the European Power Exchange (EPEX Spot) [19]. Additionally, CO_2 emissions were estimated using an average grid emission factor of 0.3 tons CO_2 per MWh [20] reflecting the energy mix of the European electricity sector. The carbon pricing used for monetizing environmental costs was €90 per ton of CO_2, based on the prevailing rates within the European Emissions Trading System (EU ETS) [21].

To assess the financial feasibility of the investment, a range of discount rates was considered, representing different potential financing conditions. Three values were selected for parametric analysis: 8%, 10%, and 12%, corresponding to low-risk, standard, and high-risk investment environments, respectively. Moreover, variations in demand growth were incorporated into the analysis, with annual growth rates of 0.5%, 1.5%, and 3%, reflecting different scenarios of energy consumption evolution and grid utilization.

Financial Analysis

The financial evaluation of the investment was conducted using NPV and BCR calculations based on Eq. 3.2.1.1 and Eq. 3.2.1.7 respectively, for a time horizon of 20 years [11]. The results are presented in Figure 26.

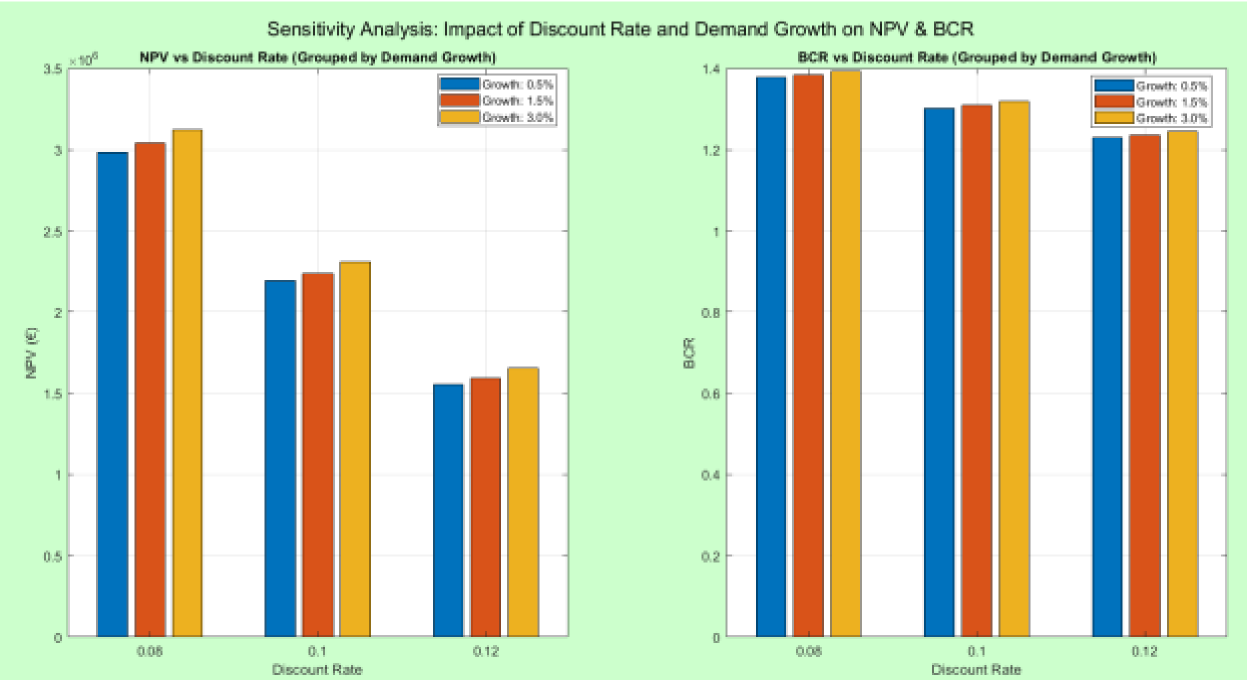

Figure 26. ***Financial Analysis for the 5-bus system test-case: Impact of Discount Rate and Demand Growth on NPV and BCR calculations***

For the New Line Addition scenario, the NPV was calculated at €2.17 million for a discount rate of 10%, indicating that the investment yields a positive economic return over its lifetime. A parametric analysis was performed to assess the impact of varying discount rates (8%, 10%, 12%) and demand growth projections (0,5%, 1.5%, 3%). The results showed that under a higher demand growth of 3% per year, the NPV could reach €3.12 million, suggesting greater economic benefits under scenarios of increasing electricity consumption. Conversely, under a higher discount rate of 12%, the NPV decreased to €1.55 million, highlighting the negative effect of higher financing costs on investment feasibility.

For the New Line Addition, the BCR was 1.3 million for a discount rate of 10%, indicating that the benefits outweigh the costs, making the investment economically justifiable. The parametric analysis revealed that under a higher demand growth scenario, the BCR increased to 1.39, while for a higher discount rate scenario, the BCR declined to 1.23. These findings suggest that investments in grid reinforcement become increasingly attractive in environments with growing electricity demand and stable financing conditions.

This initial test-run under a mock-up scenario validates the applicability of the GIPA methodology in assessing the impact of grid investments, given the provided inputs (Figure 24). Future applications of this methodology will be extended to real-world distribution networks and potential investment scenarios within the scope of the project, ensuring that grid planning aligns with the evolving energy landscape and regulatory frameworks across site via the EVELIXIA platform.

3.2.1.4 Next Steps

The next steps should focus on implementation, validation, and integration of GIPA within the project's associated services and relevant pilot sites. The proposed action plan by the end of the task (i.e., M33) is the following:

- Finalize the GIPA computational framework and refine the KPI list (**Table 1**), based on feedback from DSOs/TSOs partners.
- Streamline a structured data exchange via the EVELIXIA Services Broker that enables seamless data extraction from IS15-iVN, in parallel with the grid modelling progress and power flow simulations.
- Iteratively engage with grid-level actors, including system operators and aggregators, to co-define scenario development and parameter definition.

3.2.2 Multi-vector Network Manager (IS12)

Background & Motivation

The primary motivation for network users to provide flexibility to the grid through Demand Response (DR) mechanisms lies in the financial incentives offered by network operators. These incentives typically take the form of cost reductions or reimbursements for adjusting energy consumption or production in response to grid needs. DR mechanisms can be categorized into two main approaches [22], [23], [24]:

- Explicit Demand Response – In this approach, the DSO offers direct financial incentives to consumers (e.g., bill reductions) and establishes contracts that require them to adjust their energy consumption or generation according to the DSO's signals. This enables direct congestion management by ensuring that consumers actively modify their energy usage in response to grid needs.

- Implicit Demand Response – This approach relies on Time-of-Use (ToU) tariffs to encourage consumers to shift their energy consumption to off-peak hours. These tariffs are designed to reflect consumption and generation patterns at the distribution network level, motivating users to modify their energy behavior based on price signals. Network operators, often in collaboration with National Regulatory Authorities (NRAs), may require electricity providers to align end-user costs with distribution grid benefits and overall system efficiency. Unlike explicit DR, implicit DR influences consumer behavior indirectly, helping to alleviate grid stress and optimize network utilization.

The MvNM tool is developed to support system operators in leveraging the flexibility potential of Distributed Energy Resources (DERs) and buildings to enhance grid planning and operations. By integrating an optimization framework, the tool enables system operators to dynamically manage DR mechanisms, reducing reliance on conventional grid reinforcement strategies and enhancing the efficiency of congestion management, energy balancing, and reserve allocation [25], [26], [27], [28].

Figure 27 illustrates the concept of the MvNM tool integration with the District Digital Twin of EVELIXIA ecosystem.

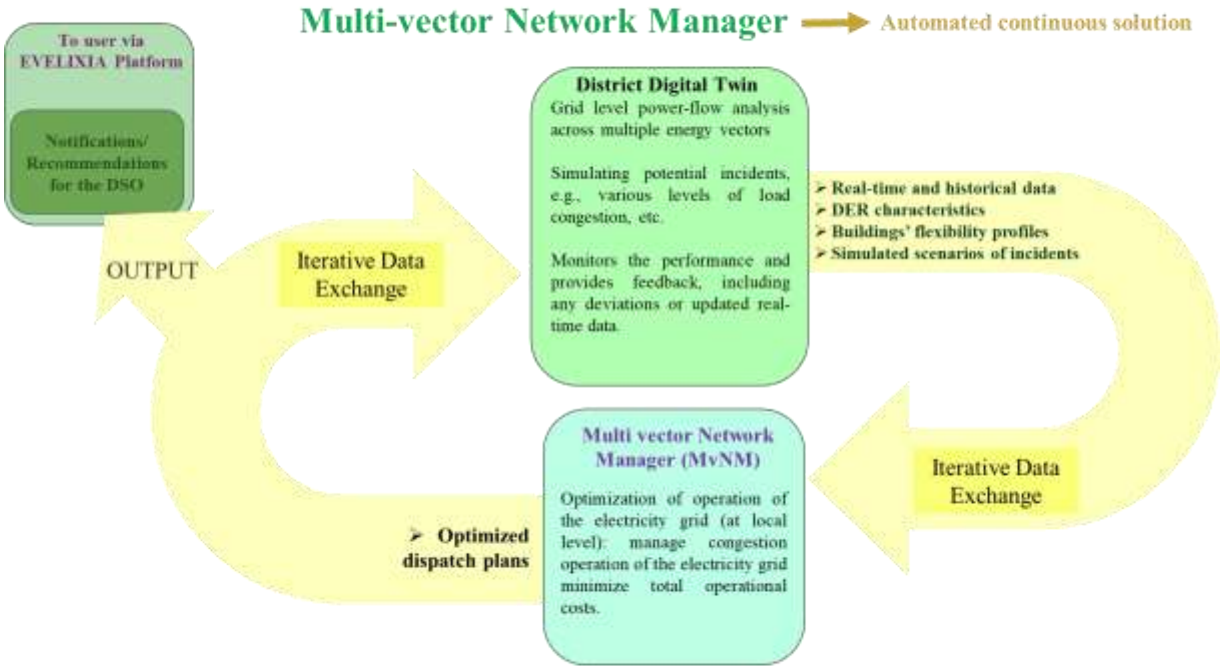

Figure 27. MvNM tool integration with the District Digital Twin of EVELIXIA ecosystem

The main idea of the tool supports optimization for both explicit and implicit demand response strategies. In explicit demand response, the DSO provides direct financial incentives to consumers in exchange for adjusting their energy usage in response to grid constraints or economic signals. In implicit demand response, ToU tariffs are designed to influence consumption patterns by encouraging end-users to shift their electricity usage to off-peak hours. Through these strategies, the MvNM tool facilitates an adaptive and cost-efficient approach to managing energy demand and supply while minimizing the need for renewable energy curtailment. However, for the purpose of the EVELIXIA project, the optimization framework of the tool only focuses on explicit demand response, in the sense that the DSO will eventually design and send cost-effective DR activation signals.

By incorporating a flexible optimization structure, the tool allows operators to evaluate and implement the most efficient flexibility allocation for different time horizons, including mid-term (daily) and long-term (monthly) grid balancing needs. This approach ensures that DER flexibility is utilized in an economically and operationally efficient manner, allowing the grid to maximize renewable energy integration while maintaining system stability.

3.2.2.1 Objectives

IS12 - Technical Objective "TRL5 to TRL7": With original functionalities developed and validated in the relevant environment of several past EU-funded projects (e.g. ONENET GA No. 957739 and MASTERPIECE GA No. 101096836), MvNM is introduced to EVELIXIA at Technology Readiness Level (TRL) 5. Advancing towards TRL6, a working version of IS12 is tested in a simplified medium-voltage (MV) distribution grid of the Greek pilot as it has been described in Section 2.2.1.3 but built in MATLBA/Simulink environment, as it is further described in Section 3.2.2.3. The final version of the MvNM will undergo validation using simulation data generated by IS15 - "intelligent Virtual Network" (iVN) (see Section 2.2.1), ensuring applicability to each pilot site network under study. As part of EVELIXIA's platform integration, progressing towards TRL 7 until the end of the project, future efforts and refinements of the tool target demonstration of the technology across EVELIXIA pilot sites, thus ensuring its applicability in balancing demand and supply without violating operational bounds of the different energy networks in real-world market designs and congestion management schemes.

IS12 - Scientific Objective: The MvNM tool is designed to optimize DR signals and leverage available flexibility resources (i.e., upward and downward power shifts on a daily basis), to support energy balance while minimizing the need for renewable energy curtailment, through cost-efficient strategies from the system operator side. The objectives of the MvNM tool are translated into functional goals that guide the tool's operation and optimization framework. These are outlined as follows:

- Shifting Towards Dynamic Grid Management and Tariff Design: Traditional long-term grid investment plans are no longer sufficient to address the dynamic challenges of modern distribution networks. The MvNM tool enables a shift towards more adaptive and flexible grid management practices by optimizing flexibility over short-term planning horizons, such as daily and monthly timescales. By incorporating short-time congestion management strategies, it enhances cost-reflective decision-making, supporting the development of adaptive tariffs and incentive mechanisms that align with E.DSO recommendations [29]. These mechanisms ensure that the cost of flexibility is accurately reflected in pricing structures, encouraging efficient energy consumption and network use.

- Enhancing Operational Efficiency: By providing DSOs with data-driven decision support, the tool enhances the overall efficiency of the distribution network. It optimizes the use of distributed flexibility to reduce the reliance on expensive infrastructure reinforcements, allowing for smarter and more sustainable grid operations. Through its optimization framework, the tool improves system efficiency by strategically allocating available flexibility resources, leading to a more reliable, cost-effective, and future-ready distribution network.
- Promoting Fairness, Transparency, and Equity in Flexibility Allocation: A key objective of the tool is to ensure fairness in how flexibility is allocated among network users. Flexibility is distributed in a non-discriminatory manner based on the actual needs and constraints of the grid, as well as the availability of resources from DERs and buildings. The tool supports transparent decision-making and equitable market participation by aligning flexibility procurement strategies with regulatory frameworks and stakeholder expectations, avoiding practices that could disadvantage specific users or locations. In practical terms, this can be ensured via a DSO that, in cooperation with the NRA, chooses the tariffs with respect to forward (e.g., day-ahead) predicted conditions [30].

3.2.2.2 Methodology

The MvNM tool is designed to optimize the flexibility potential of DERs and buildings, enabling system operators to manage grid congestion and maintain system cost-efficiency (i.e., minimizing the overall system operational costs, such costs associated with DR activation and generation curtailment). The problem focuses on day-ahead optimization for a single day (i.e., the next day), which is a practical approach, reducing computational complexity while retaining the temporal granularity needed to analyze hourly variations.

The problem represents a decision-making strategy of the DSO, focusing on applying appropriate cost penalties to maximize the operational efficiency of the network by minimizing costs for demand and generation curtailment that needs to be resorted for the security preservation of the network. The cost penalties (€/MWh) represent monetary compensation (in €/MWh) to incentivize participants to consume more or less energy. The distribution tariff structure transfers part of the network costs to the network users (consumers/prosumers), which may vary temporally and spatially. Although not directly dealing with the network tariff type, the cost penalties are designed similarly to volumetric tariffs (€/MWh). This variability is designed to signal prosumers about the cost of their energy usage or generation at specific times and locations, encouraging more efficient usage patterns and reducing strain on the grid. It also allows the DSO to account for local network constraints and operational costs.

Upward flexibility refers to the ability to increase demand or energy consumption at a network node when requested by the DSO. This might be required to balance excess generation (e.g., from renewable sources like solar or wind) or stabilize the grid during low-demand hours. Downward flexibility refers to load reduction. The flexibility providers (via aggregators) react to these requests (DSO signals) by optimizing their demand response actions, i.e., adjusting the flexibility limits according to the maximum revenue.

The optimization framework can accommodate variable cost penalties trends (from the system operator's point of view) that reflect the network needs. For example, an upward flexibility increasing penalty trend indicates a time-dependent cost structure, where the cost of upward flexibility increases during certain hours, reflecting higher system demand or reduced availability of flexibility during those hours and market conditions where upward flexibility is more expensive due to limited resources or high opportunity costs. On the other hand, as regards downward flexibility decreasing penalty trend, the penalty values are highest during morning-mid-day hours and gradually decrease throughout evening-night and early morning, suggesting that it is more costly to reduce demand during peak hours and less costly during later hours (likely off-peak). The downward flexibility penalty is typically used as an economic disincentive for the DSO to prevent demand reduction when it is less efficient or not beneficial for the system. For instance, during peak solar generation hours, reducing demand may not be efficient because it could lead to excess energy curtailment. In addition, a variable RES curtailment penalty can be used based on the cost of lost energy and time-of-day variations or market conditions.

The tool optimization framework is depicted in Figure 28.

The process begins by initializing parameters and constants, which include the hourly demand profiles of network users, renewable energy generation forecasts, and grid capacity and congestion limits (for the EVELIXIA project, these inputs are derived for the iVN simulation engine, IS15). Additionally, the flexibility potential of DERs and buildings is incorporated, representing their upward and downward flexibility margins (for the EVELIXIA project, this input is derived from the Flex Forecasting tool, IS4). These parameters form the foundation for determining the flexibility activation strategies required for grid balancing.

Following initialization, the optimization problem is structured for a 24-hour horizon, where flexibility penalties are assigned to upward and downward energy shifts. At this step, the parametric analysis setup is parametrized to account for varying flexibility margins across different nodes and penalty multipliers for upward flexibility, thus enabling the tool to evaluate multiple scenarios under different flexibility and pricing conditions, if needed.

Before the optimization algorithm, the pre-optimization step is performed to compute excess renewable energy generation from distributed sources such as PV or wind. This step identifies the available upward flexibility margins for each network node and calculates the amount of excess energy that can either be utilized through demand response or curtailed when necessary. The input is the power flow analysis for the initial state of the network (baseline profiles, congestion), conducted by the simulation engine.

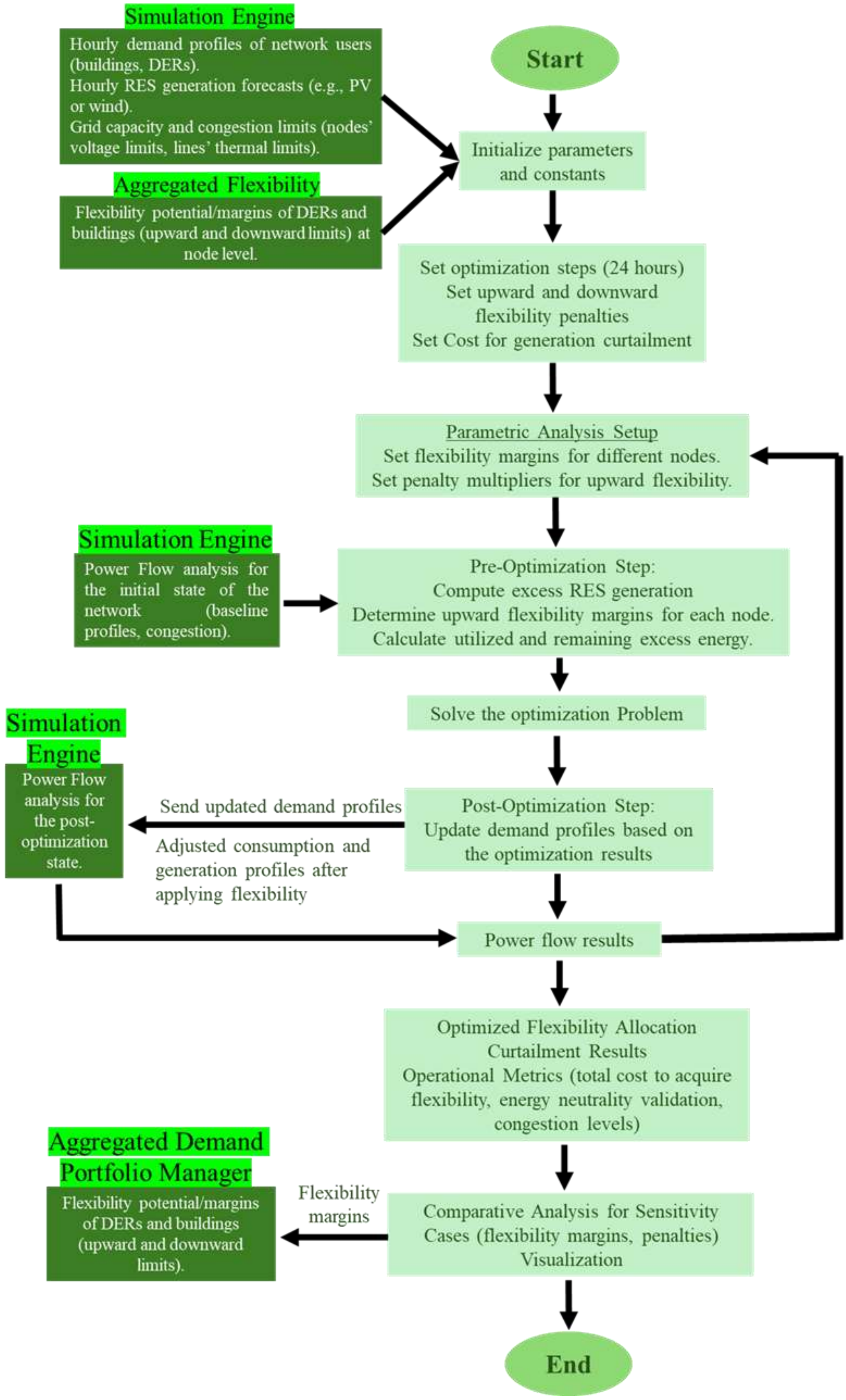

Figure 28. MvNM flowchart

The optimization problem is formulated as a cost minimization function that aims to minimize the operational costs associated with three key corrective actions: generation curtailment, upward flexibility activation, and downward flexibility activation, which can be defined as follows:

$$minC_{op} = \sum_{h=1}^{H}\left(a_1 P_{curt,h} + a_2 P_{flex-up,h} + a_3 P_{flex-down,h}\right) \qquad \text{Eq. 3.2.2.1}$$

where C_{op} represents the total operational cost, $P_{curt,h}$ is the curtailed power at hour h, $P_{flex\text{-}up,h}$ is the power shifted upward, and $P_{flex\text{-}down,h}$ is the power shifted downward. The parameters a_1, a_2, a_3 are weight factors reflecting the cost priorities for curtailment, upward flexibility, and downward flexibility, respectively, which are designed by the DSO.

The MvNM tool's optimization process is formulated as a linear programming problem, enabling efficient flexibility allocation, ensuring cost-effective grid balancing while respecting operational constraints such as energy neutrality, congestion limits, and demand flexibility bounds.

The optimization problem considers multiple constraints to ensure feasibility and reliability in the power network. Energy neutrality is enforced by ensuring that the total upward and downward flexibility adjustments balance out over the defined time horizon (energy shifts maintain a net-zero impact over the 24-hour period), as follows:

$$\sum_{h\in H}(P_{flex-up,h}) = \sum_{h\in H}(P_{flex-down,h}) \qquad \text{Eq. 3.2.2.2}$$

Flexibility bounds are imposed to limit the activation of demand response resources within predefined margins. The upward and downward shifts are restricted by the maximum available flexibility at each node, ensuring that network constraints are not violated:

$$0 \leq P_{flex-up,h} \leq P_{max-up,h}\,,\ \ 0 \leq P_{flex-down,h} \leq P_{max-down,h} \qquad \text{Eq. 3.2.2.3}$$

where $P_{max\text{-}up,h}$ and $P_{max\text{-}down,h}$ are the maximum available flexibility to increase above and reduce below baseline consumption at each node, respectively.

Additionally, curtailment limits are established to prevent excess renewable generation from being curtailed beyond the available capacity:

$$0 \leq P_{curt,h} \leq P_{res-gen,h} \qquad \text{Eq. 3.2.2.4}$$

where $P_{res\text{-}gen,h}$ is the renewable energy generation available at hour h.

The optimization framework also accounts for network constraints, ensuring that power balance is maintained across the grid. Time-specific flexibility allocation is introduced to allocate downward flexibility during predefined compensation periods, ensuring that flexibility adjustments are scheduled efficiently over the daily horizon (e.g., $P_{flex\text{-}down,h}$ during compensated hours equals $P_{flex\text{-}up,h}$ during upward shift hours).

To manage congestion, the optimization ensures that power flows do not exceed the network's thermal and voltage constraints, imposing the following condition:

$$0 \leq P_{grid,h} \leq P_{grid-max,h} \qquad \text{Eq. 3.2.2.5}$$

where $P_{grid\text{-}max,h}$ represents the maximum permissible grid capacity.

Finally, the cost penalty structure prioritizes flexibility activation over curtailment by enforcing:

$$a_1 \gg a_2, a_3 \qquad \text{Eq. 3.2.2.6}$$

which ensures that the system always seeks to utilize available flexibility before resorting to renewable energy curtailment (based on Eq. 3.2.2.1).

Once the optimization problem is solved, a post-optimization step updates the demand profiles to reflect the optimized flexibility allocation. The results, including the final flexibility shifts, curtailment levels, and operational costs, are assessed, and power flow analysis is conducted to validate the network's post-optimization state.

The tool then performs a comparative analysis across different predefined configurations, evaluating the impact of varying flexibility margins and penalties. These outputs can serve as input in the Aggregated Demand Portfolio Manager tool (IS13), which is described in Section 3.2.3.

The final outputs include the optimized flexibility allocation, curtailment results, updated load profiles, and key operational metrics such as the total cost of acquiring flexibility for the DSO, validation of energy neutrality, and congestion levels.

3.2.2.3 Evaluation & Results

Case study network set-up

For the evaluation of the MvNM tool functionality, a case study has been set up and tested, regarding grid flexibility and congestion management from the DSO side. The network under study has been built in MATLBA/Simulink environment, to represent a medium-voltage (MV) distribution grid where different types of loads and DERs interact under the coordination of a high-voltage/medium-voltage (HV/MV) substation. The purpose of this setup is to assess how the developed tool can optimize flexibility provision, minimize RES curtailment, and support congestion management through demand-side response.

The simplified network is based on the Greek pilot site of the project (derived from EVELIXIA Deliverable D1.3: Pilot Site Surveys results, Use Cases definition and market needs analysis), as it is described in Section 2.2.1.3. Given that at the time that IS12 was tested the grid modelling in iVN was under development, so, for IS12 validation purposes, the network was built in MATLAB/Simulink R2024a (using the same static data and only including electricity grid modelling). The test-network includes four nodes; at the center of the system is Node 1, the HV/MV substation, which acts as the main interface between the high-voltage (HV) transmission grid and the MV distribution network. This node is responsible for monitoring the overall load, detecting congestion, and managing flexibility bids (by the DSO) across the connected nodes. It plays a key role in balancing supply and demand, ensuring that available flexibility is used efficiently before resorting to more expensive or disruptive measures such as curtailment or external reserves.

Two major loads are connected to the MV network; Node 2, representing a research institute (namely CERTH/CPERI Building), is characterized by its potential to provide upward and downward flexibility, meaning that it can shift its electricity consumption in response to system needs. This node actively reports its load patterns and any available flexibility resources, such as on-site battery storage or controllable demand. In contrast, Node 3, which represents a hospital (namely Mpodosakeio Hospital), is categorized as a critical load. Due to its essential nature, its ability to reduce consumption is limited, but it may still offer some flexibility through backup generation or storage assets. The priority for this node is to ensure a reliable and uninterrupted power supply, while still participating in grid-balancing mechanisms when possible.

Node 4 represents the aggregated PV plants' production connected to the MV network, offering power generation data and potential flexibility through curtailment services. Under normal conditions, the PV plants operate at maximum production with minimal restrictions. However, during congestion or imbalances, the output can be curtailed to maintain system stability. Ideally, instead of curtailment, the tool aims to redistribute excess PV generation by utilizing available flexibility from Nodes 2 and 3, ensuring a more efficient use of renewable energy.

The developed tool integrates this grid setup into its optimization framework, allowing the DSO to evaluate different flexibility procurement strategies (i.e., design appropriate electricity tariffs and incentive-based mechanisms). By leveraging the load-shifting capabilities of Nodes 2 and 3, the tool determines the optimal allocation of flexibility, prioritizing cost-efficient solutions that minimize unnecessary PV curtailment. The optimization also considers economic factors, assigning flexibility provision based on the cost-effectiveness of different nodes.

Case study implementation

At the first step of the tool's implementation, the input data from the simulation environment (which in this case is MATLAB/Simulink, performing the power flow analysis of the network under study) is loaded to define the conditions of the selected grid operation scenario. The primary inputs include the hourly electricity demand for Node 2 (representing a research institute) and Node 3 (representing a hospital), as well as the PV generation at Node 4. The demand values provide the baseline energy consumption of the research institute and the hospital, while the PV generation data indicates the available renewable energy supply that could potentially be curtailed or redistributed depending on grid conditions. Beyond demand and generation data, the tool also incorporates predefined flexibility margins for Nodes 2 and 3. These margins define the extent to which each node can adjust its electricity consumption in response to system requirements. By applying these margins, the tool calculates the upper and lower bounds for potential shifts in demand. The upper bound represents the maximum additional consumption that can be accommodated, while the lower bound determines the minimum consumption level that can be maintained while still providing downward flexibility. By varying these margins, the tool can explore how flexibility availability impacts grid operations.

For the Greek network case study, the penalties applied in the optimization process were designed to balance flexibility activation costs and minimize renewable energy curtailment. The penalty values used are i) the Upward Flexibility Penalties, applied to the cost of increasing demand at specific network nodes when required by the Greek DSO; the values were dynamically adjusted using a penalty multiplier, which scaled the base penalty values for upward flexibility at each node, ii) the Downward Flexibility Penalties, used to discourage excessive load reduction when it was not beneficial for the system; the penalty values followed a decreasing trend, where they were highest during peak hours (morning and mid-day) and gradually reduced during off-peak periods (evening and night) and iii) the Renewable Energy Curtailment Penalty – a fixed penalty of 115 €/MWh was applied [30], to minimize curtailment of RES; this penalty discouraged the tool from resorting to curtailment unless flexibility resources were insufficient to absorb the excess generation. The integration of these penalties into the cost function of the optimization model, allows the tool to test scenarios where increasing consumption is either cheap or expensive, influencing the optimization process. As results, the practical value of these cost penalties for the Greek DSO (HEDNO) lies in the following aspect: a) Testing Grid Behavior Under Different Scenarios: By varying the flexibility margins and penalties, the tool can simulate how Nodes 2 and 3 respond to different levels of flexibility availability and cost. HEDNO can use these insights to design optimal flexibility strategies, such as encouraging flexibility participation from nodes with lower penalties and identifying the impact of tighter flexibility margins on grid stability, b) Policy and Tariff Design: The penalty multipliers can help HEDNO evaluate the financial implications of different pricing strategies for flexibility services.

Another key aspect of the input processing is the estimation of excess PV generation. The tool calculates the difference between the PV output at Node 4 and the combined demand at Nodes 2 and 3. If PV generation exceeds local consumption, the tool identifies this surplus as potential excess energy that could be curtailed if no flexibility is available to absorb it. To avoid unnecessary curtailment, the tool simultaneously evaluates the total available flexibility from the research institute and the hospital, determining how much of the excess energy can be reallocated rather than curtailed. It is noted that the input data regards several different days responding to multiple conditions of the network under study. Figure 29 illustrates the input data for one indicative day, in which the PV generation excess demand for certain hours within a day.

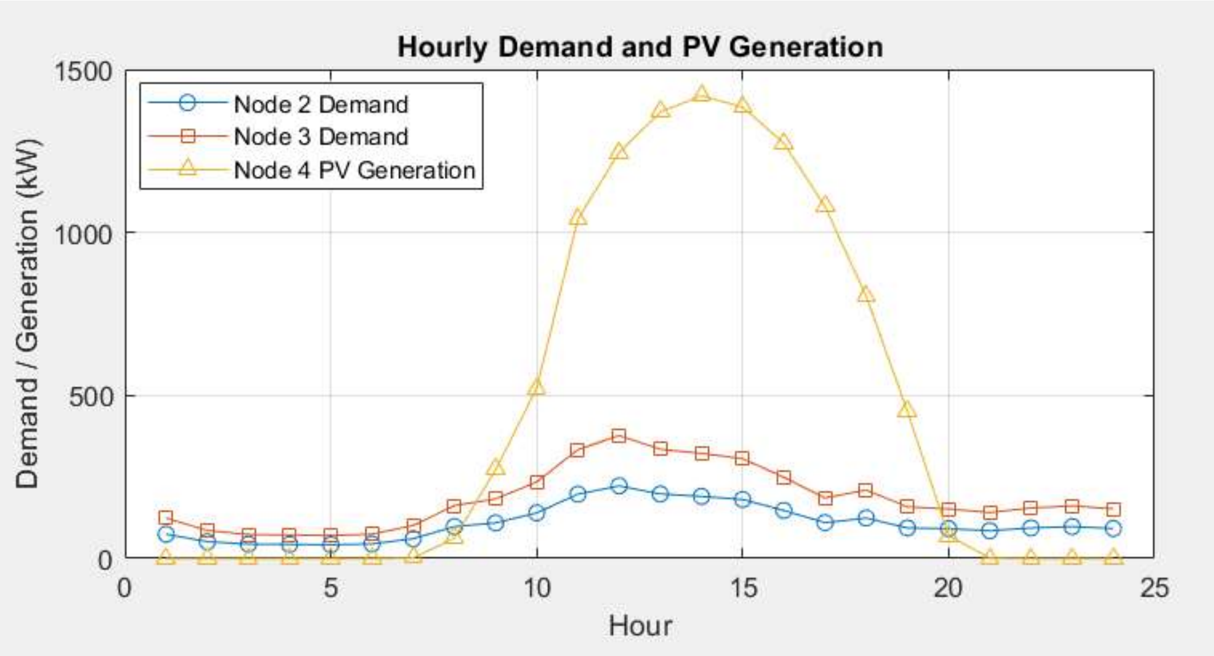

Figure 29. Hourly Demand (Nodes 2 and 3) and PV Generation (Node 4) for the network under study, for a selected day

Figure 30 depicts the flexibility margins considered in this case study for Nodes 2 and 3, equally set to 15% around the baseline consumption of the nodes.

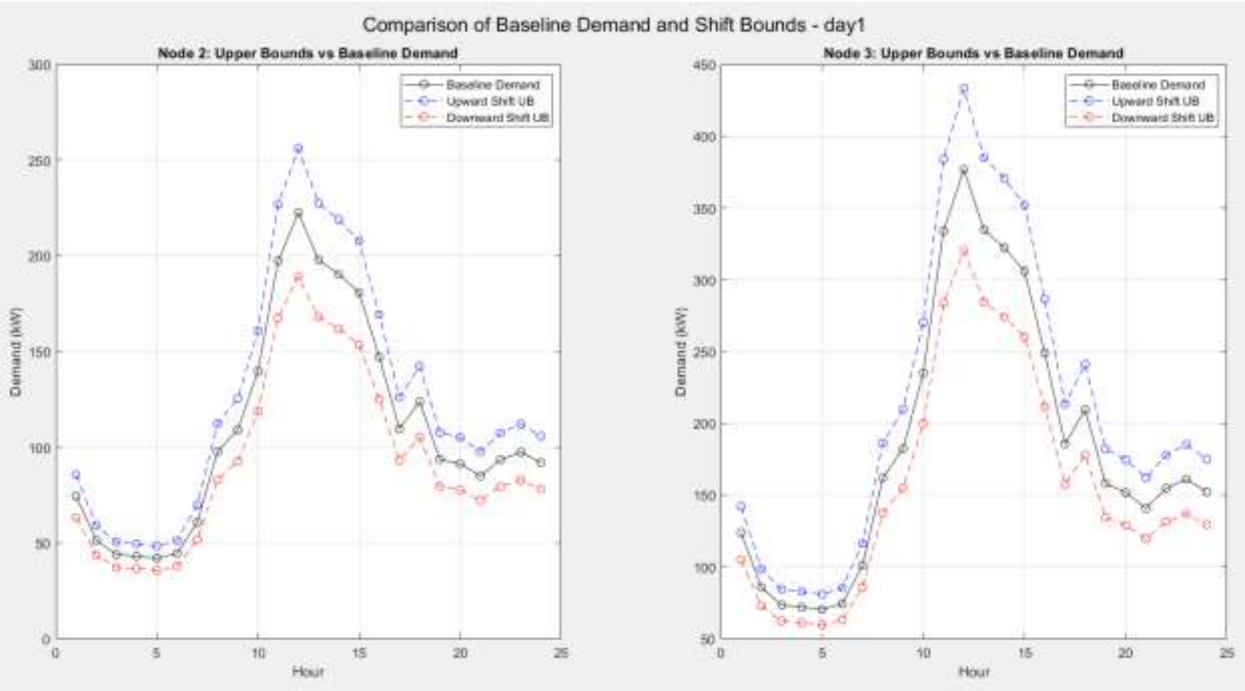

Figure 30. Comparison of the baseline demand (Nodes 2 and 3) and shift upward and downward bounds for the network under study, for a selected day

Finally, Figure 31 presents the potential utilization of the excess PV energy if maximum upward flexibility from Nodes 2 and 3 is activated at the specific over-production timeframes.

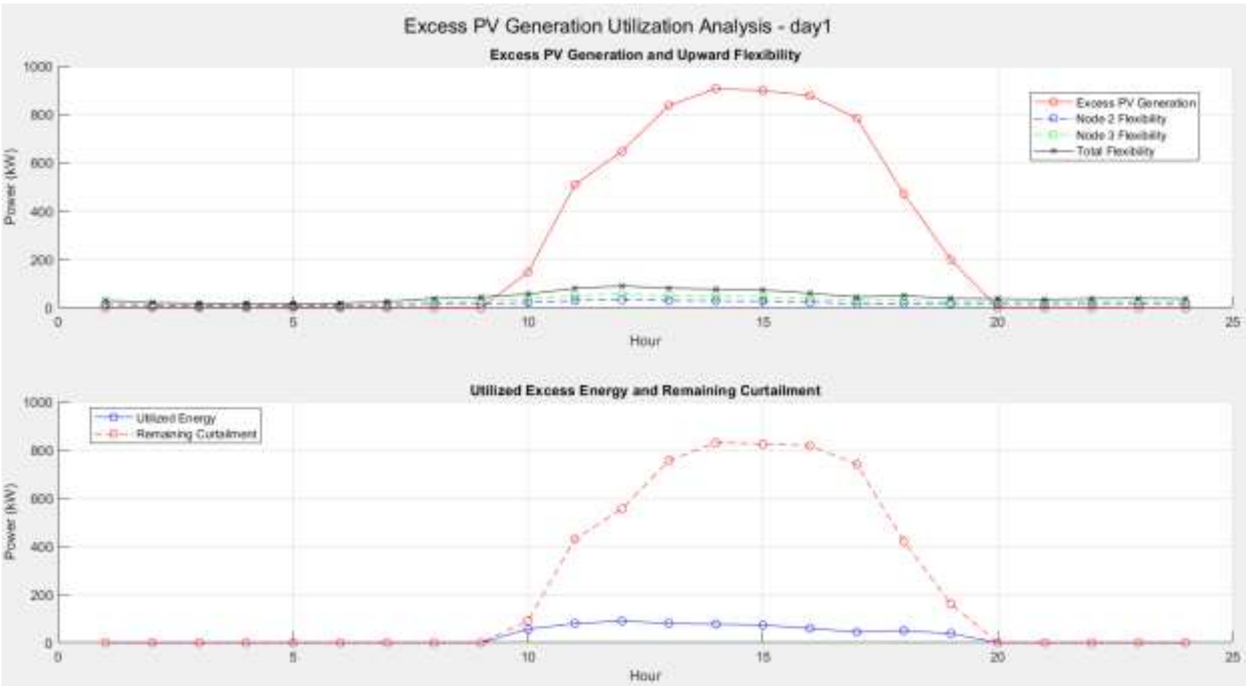

Figure 31. Potential utilization of the excess PV energy if maximum upward flexibility from Nodes 2 and 3 is activated (based on Figure 29 and Figure 30)

These outputs are the necessary input for the next stage of the tool, where the optimization process will determine the most efficient way to allocate flexibility resources and minimize curtailment, while ensuring grid economic viability from the DSO perspective.

Moreover, at this step, the tool processes the pre-optimization power flow results to assess the baseline power flow conditions before any flexibility allocation or optimization adjustments are applied. This serves as a reference point for comparison with the post-optimization power flow, helping to evaluate the impact of flexibility on grid operation. The tool establishes key system constraints related to voltage and power flow limits. The upper and lower voltage bounds for this case study are set at 1.05 pu and 0.95 pu (common standards, valid for the Greek network), respectively, ensuring that voltage levels remain within acceptable operational limits. Additionally, power flow constraints are imposed, restricting active power transfer at higher levels than the line capacity (set to 500 kW for the case study), representing the allowable range for the transmission line capacity for the case study.

Next, the optimization step in the Greek case study for the MvNM tool is implemented to manage flexibility allocation and PV curtailment while minimizing operational costs for the system, managed by the DSO. The goal is to maximize the use of available flexibility at the two nodes of the network, activating their flexibility capabilities to absorb excess PV generation and maintain the balance of the grid in the most cost-efficient way.

In this case, the decision variables of the optimization problem (formulated as a linear problem in Eq. 3.2.2.1) include the upward and downward shifts in demand at the two nodes, as well as PV curtailment. Upward shifts represent an increase in demand at a given hour, allowing the system to absorb excess PV generation, whereas downward shifts compensate for these adjustments at different times to maintain energy neutrality within the daily horizon. PV curtailment is only introduced when flexibility is insufficient to fully accommodate the excess PV generation.

The optimization process is subject to several constraints. A power balance constraint ensures that at each hour, the sum of flexibility adjustments and PV curtailment matches the available excess PV generation. In cases where flexibility alone is insufficient, PV curtailment is activated. The problem formulation also includes energy neutrality constraints, requiring that any upward shift in demand at a node is later compensated by a downward shift over the optimization period. This ensures that no net energy imbalance occurs at the end of the day. This allows the system operators to manage effectively not only PV curtailment, but also load congestion that usually occurs during late evening timeslots. Thermal constraints are also incorporated into the problem, ensuring that power flows performed in the simulation environment remain within the maximum allowable line capacity. The flexibility at each node is further constrained by the predefined margins (in this case 15% for both upward and downward flexibility for both nodes under study), which limit the extent to which demand can be shifted up or down.

The cost function in this optimization is formulated to minimize the total cost of utilizing flexibility and PV curtailment. The penalties for activating flexibility are applied dynamically, with economic allocation ensuring that the node with the lower penalty is allocated more power. This economic prioritization follows an inverse relationship between penalty values and flexibility allocation, ensuring cost efficiency in the optimization process. Additionally, PV curtailment carries a fixed high penalty cost, encouraging the system to utilize flexibility as much as possible before resorting to curtailment.

The problem for the present tool implementation is solved using a linear programming approach, where the objective function is minimized while satisfying all equality and inequality constraints. The MATLAB linprog solver is used to compute the optimal values for flexibility activation and PV curtailment. The solution provides the optimal flexibility schedule for both nodes, the total flexibility cost, and the amount of PV curtailment required. If the solver successfully converges, the results are post-processed to validate energy neutrality, ensuring that upward and downward flexibility adjustments balance over the day. The optimized flexibility and curtailment results for this case are visualized Figure 32.

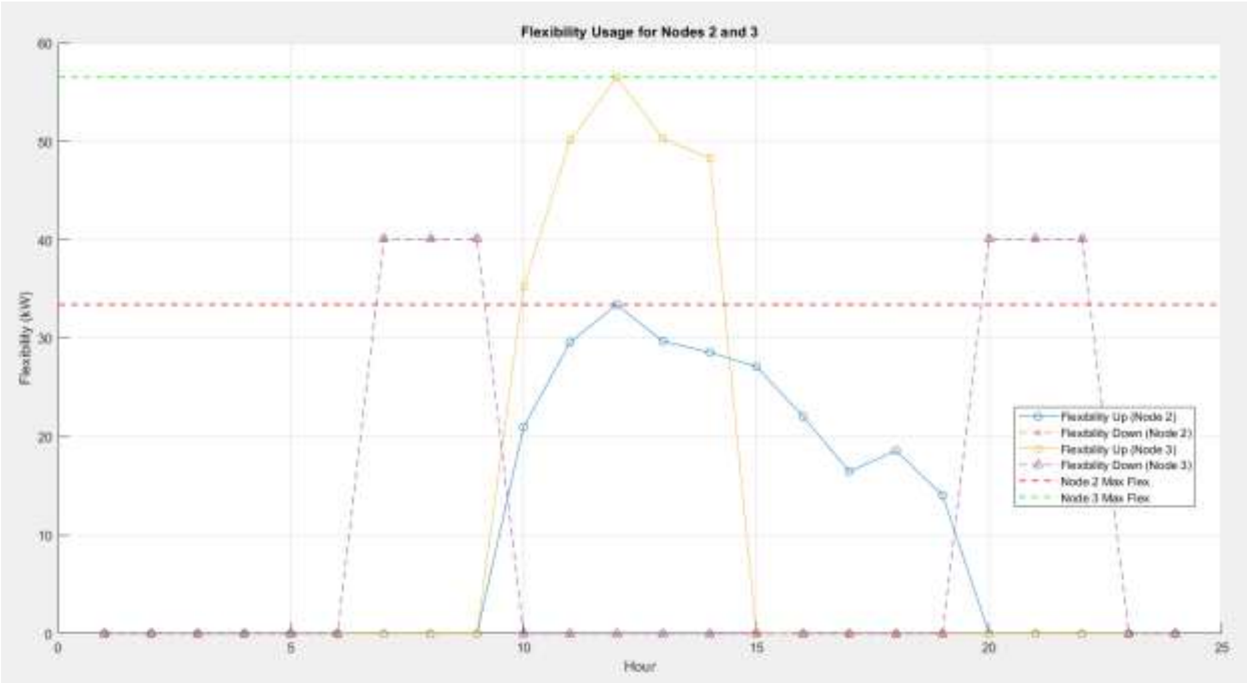

Figure 32. Optimized flexibility and curtailment results (Nodes 2 and 3) for the network under study

The results presented in Figure 32 are send to the simulation environment, to perform again the power flow analysis, using the optimized consumption curve for the load nodes (Nodes 2 and 3) and the optimized PV production curve (Node 4). The power flow results with the updated set-points are sent back to the MvNM tool, for the post-optimization power flow evaluation. These results are presented in Figure 33, Figure 34 and Figure 35.

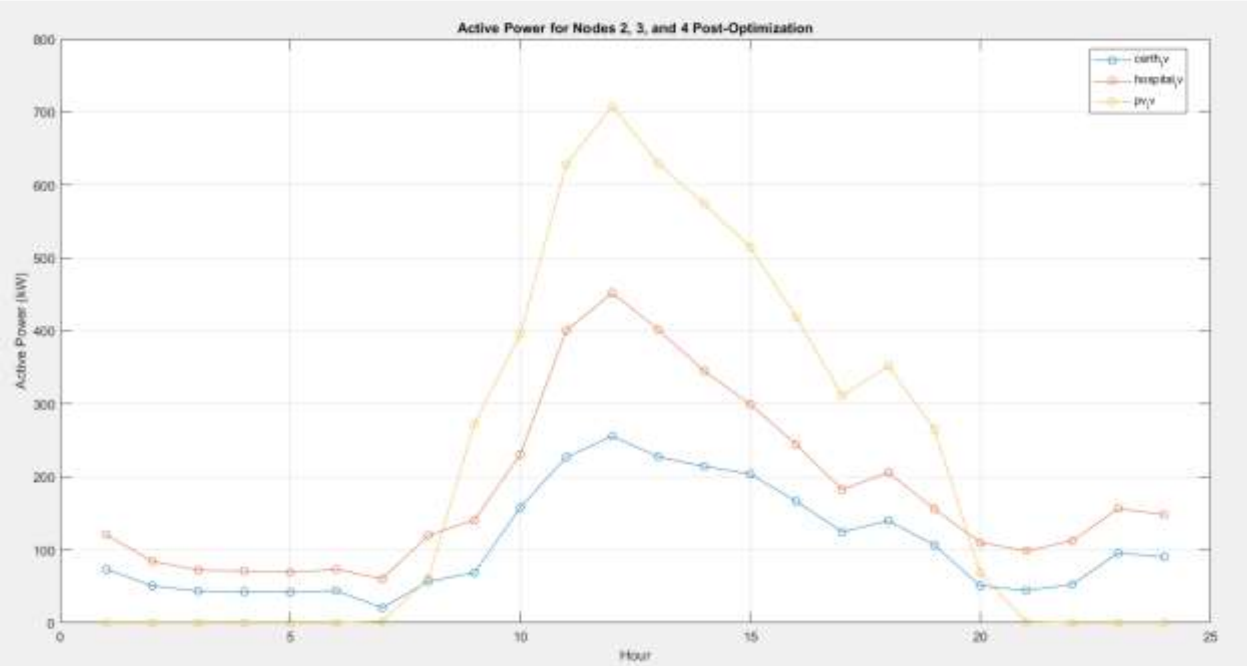

Figure 33. Post-Optimization power flow results for the network under study: Active power flow for Nodes 2, 3, and 4

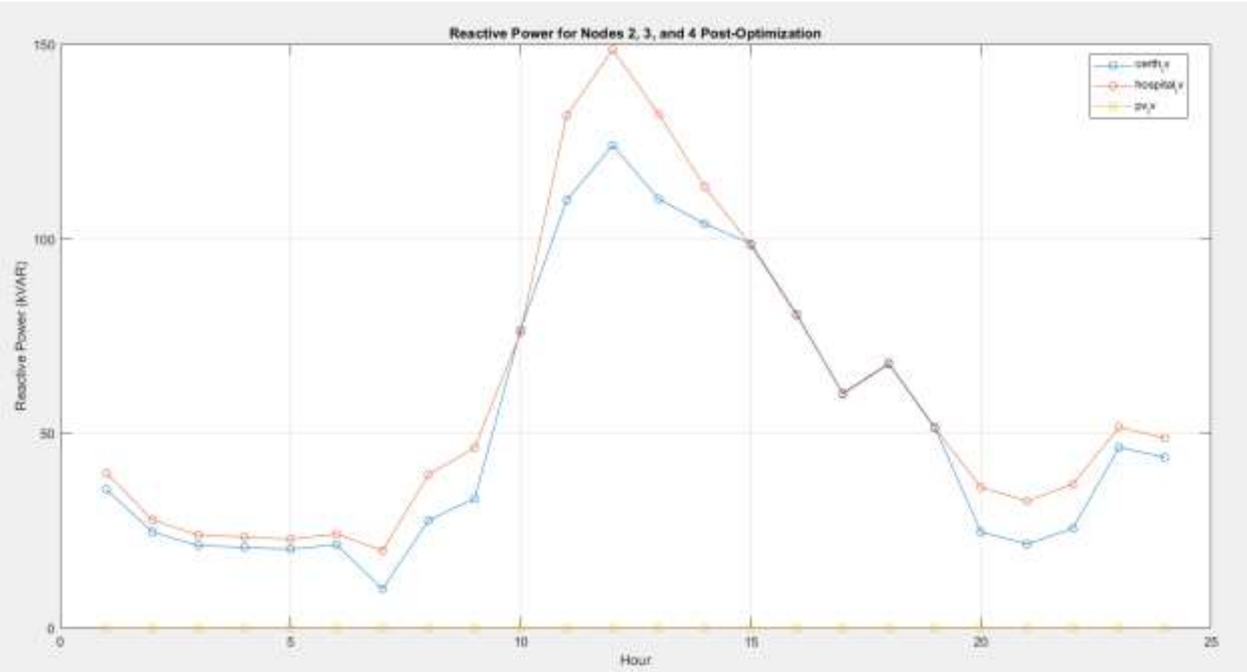

Figure 34. Post-Optimization power flow results for the network under study: Reactive power flow at Nodes 2, 3, and 4

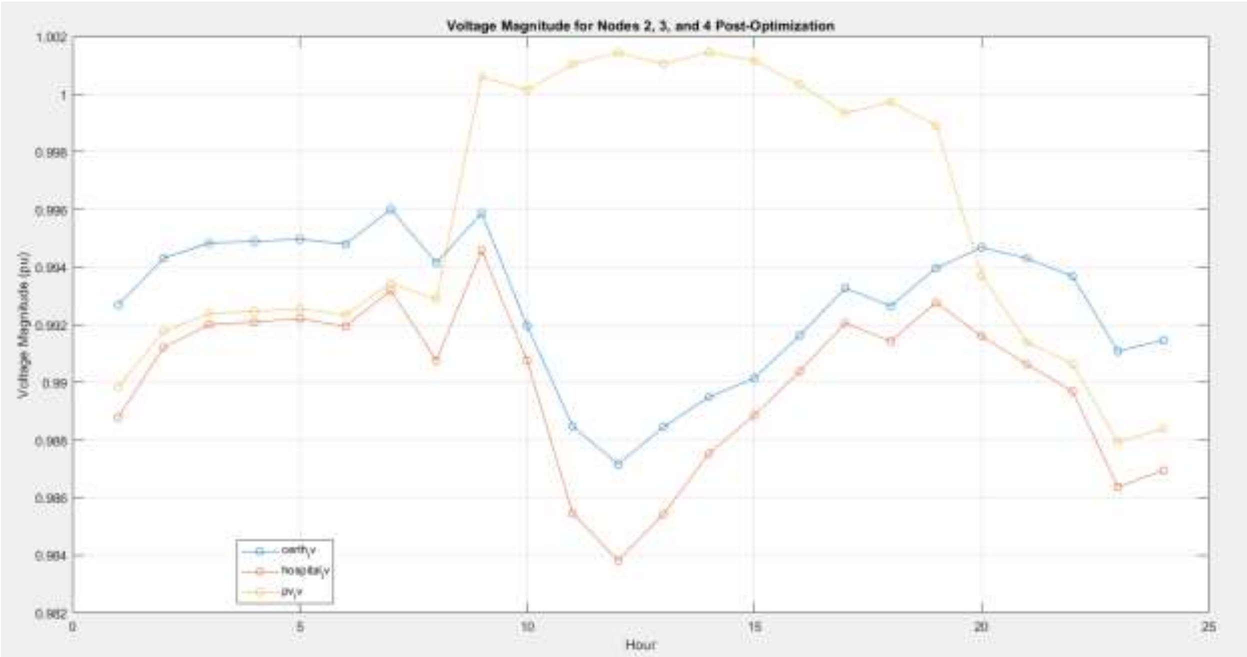

Figure 35. Post-Optimization power flow results for the network under study: Voltage magnitude – in per unit (pu) – at Nodes 2, 3, and 4

The variation of the power consumption for both flexible nodes after the optimized set-points compared to their baseline consumption, as well as the curtailed PV generation set points are depicted in Figure 36, Figure 37 and Figure 38, via a comparison between the pre-optimization power flow simulation results and the post-optimization power flow simulation results.

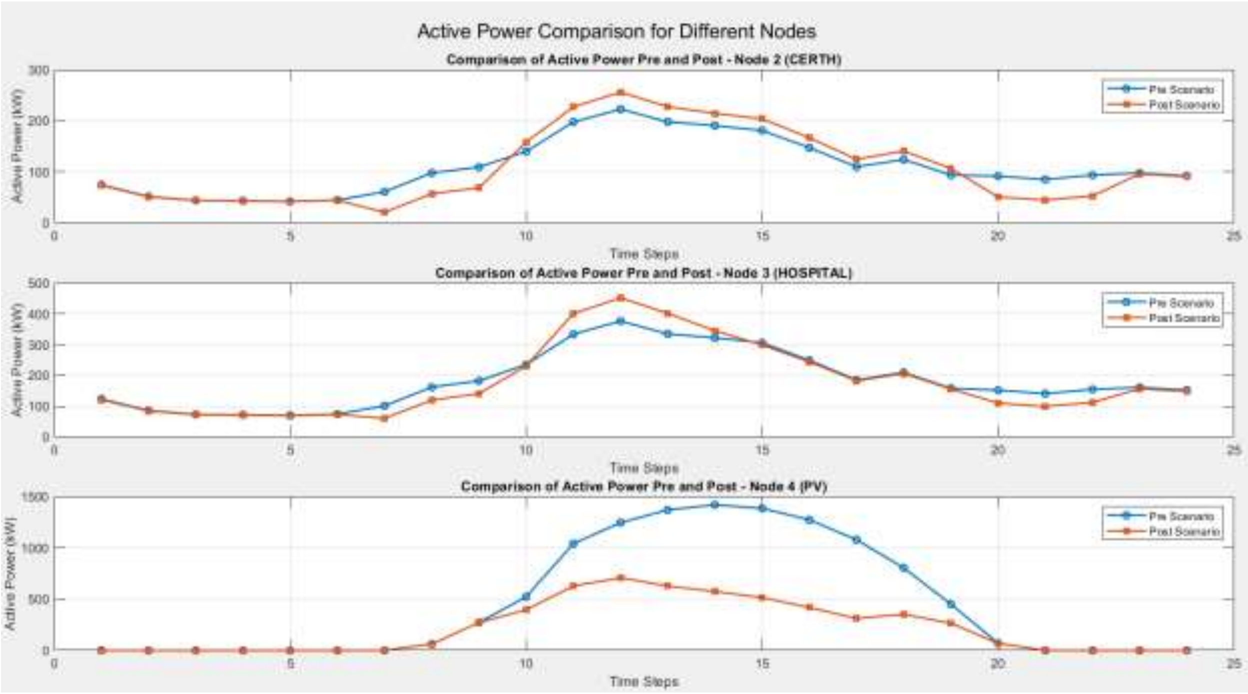

Figure 36. Pre and Post-Optimization power flow results for the network under study: Active power flow for Nodes 2, 3, and 4

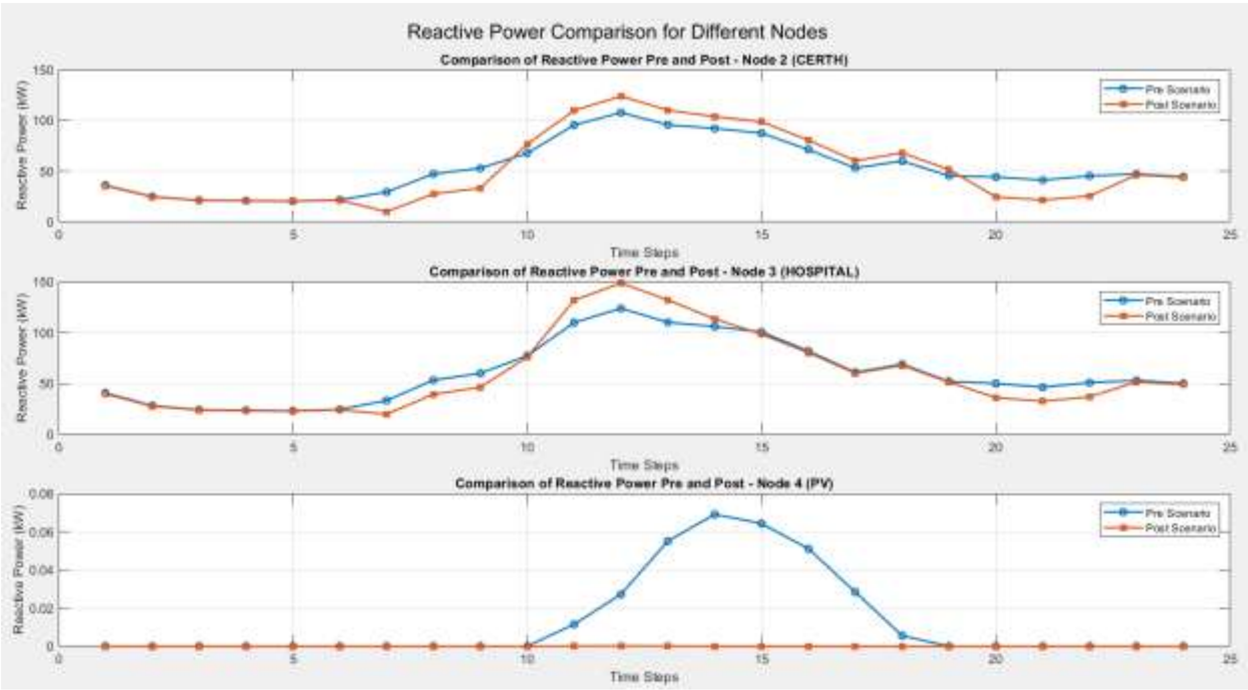

Figure 37. Pre and Post-Optimization power flow results for the network under study: Reactive power flow for Nodes 2, 3, and 4

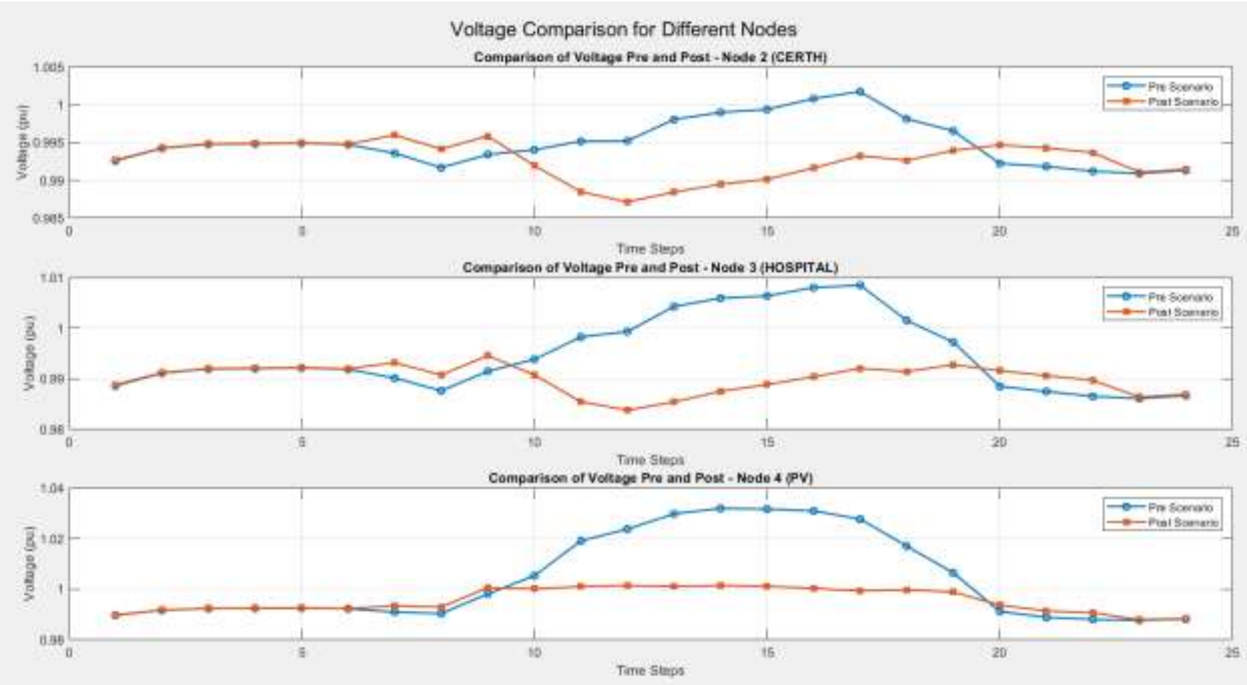

Figure 38. Pre and Post-Optimization power flow results for the network under study: Voltage magnitude – in per unit (pu) – at Nodes 2, 3, and 4

As Figure 36 and Figure 37 show, the optimized active and reactive power flows at node ensure energy balance in the network under study, exploiting the maximum available flexibility of the loads to absorb the PV generated energy during high production hours. As a result, the voltage profile after the optimization at every node is improved (i.e., reduced overvoltage).

Overall, the presented case study verifies the MvNM optimization framework can effectively integrate demand flexibility to manage excess RES generation, ensuring cost-efficient grid operation while maintaining system constraints and minimizing unnecessary curtailment. Although simplified, the case under study proves the validity of the optimization process of the tool.

3.2.2.4 Next Steps

The next steps should focus on implementation, validation, and integration of MvNM within the project's associated services and relevant pilot sites. The goal is to ensure that the tool optimally allocates flexibility, supports congestion management, and reduces grid operational costs while complying with existing market and regulatory frameworks. The proposed action plan by the end of the task (i.e., M33) is the following:

- Streamline a structured data exchange via the EVELIXIA Services Broker that enables seamless data extraction from IS15-iVN, in parallel with the grid modelling progress and power flow simulations.
- A structured data exchange will enable seamless data transactions between the MvNM and other ISs (IS4, IS13 and possibly other), as described in the methodology.
- Iterative engagement with grid-level actors, including system operators and aggregators, to co-define scenario development and parameter definition. For practical validation, the tool must be integrated into an operational DSO network or microgrid where real-time grid data is continuously fed into the system (this should be done via the district digital twin of the project). The system operators for the pilot sites should provide feedback on the tool's usability and effectiveness, enabling refinements based on real-world operational insights. Since the tool integrates cost penalties and flexibility bids, it is crucial to assess its response to variations in electricity prices from market platforms such as EPEX Spot and Nord Pool. Different day-ahead and intra-day electricity price signals should be introduced where relevant to evaluate whether the tool can optimize demand-side participation.

3.2.3 Aggregated Demand Portfolio Manager (IS13)

Modern energy grids are increasingly challenged by the need to balance supply and demand while integrating renewable sources and ensuring operational efficiency. Variations between the predicted and actual energy consumption at the building level can lead to grid instability, increased operational costs, and underutilization of available distributed energy resources. At the same time the consumption profiles of buildings can be deviated at some extend, still sustaining the thermal comfort behaviour of occupants. This way there are needs to be fulfilled from the building's side and requests that would alleviate the efforts to be performed from the DSO side avoiding stress and congestion in the grid. The Aggregated Demand Portfolio Manager (ADPM) serves as an intermediate stage between the two aforementioned sides aiming to enable day-ahead modifications on the consumption profile schedule, i.e., re-dispatch operation. By leveraging aggregated building data and integrating dynamic demand response signals from

Distribution System Operators (DSOs), ADPM plays a critical role in supporting grid balancing at the district scale.

Therefore, the ADPM service builds upon the growing body of research that emphasizes the importance of flexible demand-side management to enhance grid resilience. Traditional optimization methods, such as mixed-integer programming, often rely on deterministic assumptions that can lead to suboptimal outcomes in a dynamic operational environment. In contrast, ADPM employs advanced episodic reinforcement learning and continuous policy-search techniques. This enables it to actively trade available supply and demand packages, plan resources more effectively, and minimize both economic and technical risks associated with grid operations. The successful integration of these methodologies is expected to enhance operational efficiency, reduce the reliance on expensive grid reinforcement, and support the broader transition towards sustainable energy systems.

Figure 39 illustrates the general workflow of this service. More specifically, Aggregated Demand Portfolio Manager is designed to aggregate baseline energy consumption predictions and building-specific flexibility bounds—ensuring that adjustments to energy consumption do not compromise thermal comfort. The tool receives inputs from individual building systems regarding their consumption behaviors and flexibility limits, as well as district-level DSO requests that specify desired adjustments along with associated incentives. Using these inputs, ADPM forms aggregated flexibility pools that allow energy aggregators and retailers to re-plan and re-schedule demand on a daily basis though recommendations.

The core of ADPM's functionality is its optimization framework, which is underpinned by a reinforcement learning approach. This framework continuously searches for and updates optimal energy trading policies in a day-ahead manner, actively fulfilling thermal comfort needs and reducing electricity bills from the users' side, while also mitigating risks and alleviating DSO's effort in congestion management. By aligning building-level flexibility with the operational constraints of the grid, ADPM ensures that the aggregated demand portfolio not only meets the grid's balancing requirements but does so in a cost-efficient and economically beneficial manner for different involved stakeholders.

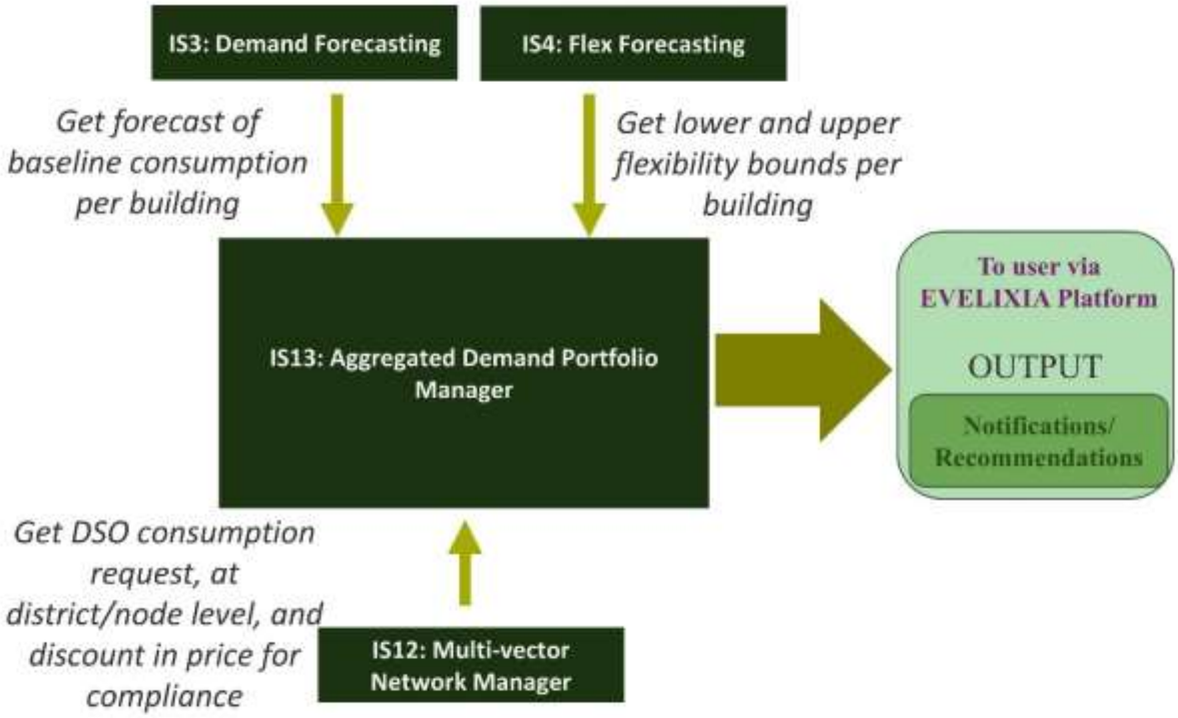

Figure 39. General scheme of Aggregated Demand Portfolio Manager

3.2.3.1 Objectives

IS13 - Technical Objective "TRL5 to TRL7": The primary technical objective of IS13 is to advance the Aggregated Demand Portfolio Manager from TRL5 to TRL7. At TRL5, the tool has been validated in controlled, simulated environments and has demonstrated its capability to process building-level energy data and integrate district-level DSO signals. The next phase focuses on robust system integration, responsiveness, and validation in real emulated grid scenarios. Key technical enhancements include: a) Integration and Interoperability; b) Robustness, and; c) Scalability and Resilience; Regarding the first point seamless interfacing with other EVELIXIA modules (e.g., day-ahead flexibility forecasting and DR response systems) is expected following NGSI-LD standards. The second point aims at enhancing the tool's computational efficiency and robustness to support energy re-schedule through recommendations, i.e., re-dispatch in dynamic grid conditions. The last part aims to demonstrate consistent performance under varying operational loads and diverse grid scenarios through pilot diverse cases. These improvements will not only enhance the tool's operational reliability but also ensure its practical applicability, paving the way toward TRL 7.

IS13 - Scientific Objective: The scientific objective of IS13 is to develop and validate an advanced decision-making framework for aggregated demand management that leverages episodic reinforcement learning. This approach aims to provide an enhanced performance compared to traditional deterministic optimization techniques by actively adapting to the dynamic and uncertain nature of energy consumption and grid conditions. One of the primary scientific pursuits is the development of advanced optimization techniques that employ continuous policy-search mechanisms. This enables active trading of flexible energy supply and demand packages in a day ahead manner. Also, this approach integrates multiple data streams—including baseline consumption predictions, building flexibility bounds, and DSO incentives—to establish an adaptive, data-driven resource planning strategy that minimizes both economic and technical risks, sustaining thermal comfort and maximizing self-consumption in cases where PV systems are included. Additionally, the reinforcement learning framework is rigorously validated in dynamic environments, effectively managing and optimizing aggregated energy portfolios under diverse operational conditions. This holistic strategy not only improves grid stability but also maximizes revenue opportunities for energy aggregators. Through this innovative approach, IS13 seeks to provide a scientifically rigorous foundation for autonomous energy management that aligns with the evolving needs of modern grid systems.

3.2.3.2 Methodology

In our approach, we adopt an episodic reinforcement learning framework to optimize the aggregated demand portfolio. In this formulation, each episode corresponds to a full day segmented into hourly intervals. At each time step t, the RL agent observes the current state—including baseline consumption, residual demand, flexibility bounds, DSO requests and incentives for fulfilling those requests and retail price tariffs—and then selects an action a_t to adjust the consumption profile. The agent's objective is to learn an optimal policy that minimizes the monetary cost while satisfying grid constraints and preserving thermal comfort.

The overall cost—and hence the reward—is designed to reflect several critical aspects of the problem:

- Residual Demand Management: Ensuring that the adjusted consumption aligns with the baseline so that the net energy balance is close to zero (before and after load scheduling).
- Price Awareness: Encouraging the agent to adhere to DSO signals when available and to extrapolate price tariffs in their absence, thereby reducing monetary costs.
- Flexibility Constraint Compliance: Penalizing deviations that would violate the flexibility bounds of individual buildings, thus maintaining thermal comfort.

Formally, the residual demand is updated as:

$$d_{t+1} = d_t + b_t - a_t \quad \text{Eq. 3.2.3.1}$$

where b_t represents the baseline consumption. The reward at time t is then defined as:

$$R_t = -\sum_{i=1}^{4} C_i \quad \text{Eq. 3.2.3.2}$$

where C_1 is the residual demand cost being aimed to produce consumption profile with close to zero energy balance before and after scheduling, C_2 serves for price awareness cost term prompting the agent to follow requests provided by the DSO if exist, and extrapolate price tariffs while there are no DSO requests, thus aiming at monetary cost reduction in both cases. Finally, C_3 and C_4 stand for the flexibility violation factors inducing penalization in cases where the reinforcement learning agent outcomes energy consumption decisions that violate thermal comfort by deviation out of the flexibility bounds.

More specifically, regarding residual demand cost, for t=23 (end of the day on an hourly basis):

$$C_1 = \begin{cases} coef_1 \cdot \frac{|d_t|}{\sum_{k=0}^{23} b_k}, d_t > 0 \\ coef_2 \cdot \frac{|d_t|}{\sum_{k=0}^{23} b_k}, d_t < 0 \\ 0, \; otherwise \end{cases} \quad \text{Eq. 3.2.3.3}$$

While for cases where t<23:

$$C_1 = \begin{cases} coef_3 \cdot \frac{|a_t - f_t^{down}|}{\sum_{k=0}^{23} b_k}, p_t > \frac{1}{6}\sum_{k=t}^{t+6} p_k \, , \\ coef_3 \cdot \frac{|a_t - f_t^{up}|}{\sum_{k=0}^{23} b_k}, \; otherwise \end{cases} \quad \text{Eq. 3.2.3.4}$$

If a distribution system operator signal is active ($DSO\_DR_t \neq 0$), C_1 is modified as follows:

$$C_1 = coef_3 \cdot \frac{|a_t - (b_t + DSO\_DR_t)|}{\sum_{k=0}^{23} b_k} \qquad \text{Eq. 3.2.3.5}$$

For the price awareness cost C_2, if $DSO\_DR_t > 0$:

$$C_2 = \begin{cases} -coef_3 \cdot a_t \cdot p_t \left(1 - \frac{Discount_t}{1+|b_t+DSO\_DR_t - a_t|}\right), if\ ratio_t > 1, \\ -coef_3 \cdot a_t \cdot p_t \left(1 - \frac{Discount_t}{1+|f_t^{up} - a_t|}\right),\ otherwise \end{cases} \qquad \text{Eq. 3.2.3.6}$$

While in the case where $DSO\_DR_t < 0$, the variable f_t^{up} is replaced by f_t^{down} in the corresponding parts of the previous equation. Also, $ratio_t = (f_t^{up} - b_t)/DSO\_DR_t$ or $ratio_t = (f_t^{down} - b_t)/DSO\_DR_t$. For the case where $DSO\_DR_t = 0$ then the cost parameter becomes: $C_2 = -coef_3 \cdot a_t \cdot p_t$.

The reward terms for penalizing the upper and lower flexibility violation are given by:

$$C_3 = \begin{cases} coef_4 \cdot \frac{|a_t - f_t^{up}|}{\sum_{k=0}^{23} b_k}, if\ a_t > f_t^{up}, \\ 0,\ otherwise \end{cases} \qquad \text{Eq. 3.2.3.7}$$

$$C_4 = \begin{cases} coef_3 \cdot \frac{|a_t - f_t^{down}|}{\sum_{k=0}^{23} b_k}, if\ a_t < f_t^{down}, \\ 0,\ otherwise \end{cases} \qquad \text{Eq. 3.2.3.8}$$

Note that $coef_{1\ldots4}$ are weighting parameters, while also $\sum_{k=0}^{23} b_k$ serves as a normalization factor using the total baseline energy in order to ensure consistent scaling. Specifically, this factor enhances stability during training, ensures proportional penalties across scenarios, and aligns the reward with real-world performance metrics.

3.2.3.3 Evaluation & Results

To evaluate the performance of the Aggregated Demand Portfolio Manager, data from the Greek pilot site were utilized. The conducted experiments were derived using the Proximal Policy Optimization (PPO) reinforcement learning algorithm. In this pilot, each node corresponds to a single building. The reinforcement learning agent was trained on five days of data and subsequently tested on three additional days. During both training and testing, the agent's objective was to produce an optimal consumption profile—referred to as the Aggregated decision—that aligns with the DSO request where applicable, respects flexibility bounds, and responds to incentive signals in the form of discounted prices.

Figure 40 and Figure 41 illustrate the behavior of the RL agent for Node 2 (CERTH) and Node 3 (Hospital), respectively, on a representative test day. Each chart plots multiple time-series:

- Down Flex Bound (blue line) and Up Flex Bound (red line): Define the allowable range of consumption that maintains thermal comfort.
- Baseline (green line): The predicted (or originally planned) consumption for each building.
- Aggregated Decision (black dashed line): The RL agent's optimized consumption profile.
- DSO Request (purple line): The desired consumption adjustment signaled by the DSO. Note that this is directly the desired trajectory to be followed by the DSO rather than the difference from the baseline.
- Price (orange dashed line): The standard retail price signal. The algorithm takes into account this price profile for those hours of the day that DSO does not produces a request. Future realizations will evaluate cases where this profile is excluded meaning that the DSO does not allow deviations even if $DSO\_DR_t = 0$.
- DSO Discounted Price (orange dotted line): The price signal with a discount applied as an incentive for following DSO requests. Notably, the DSO Discounted Price applies the full discount only when the building or aggregator fully meets the requested consumption adjustment. If the request is only partially fulfilled, a proportionally reduced discount is applied (e.g., via linear interpolation). This design encourages complete compliance with the DSO request to maximize financial benefits.

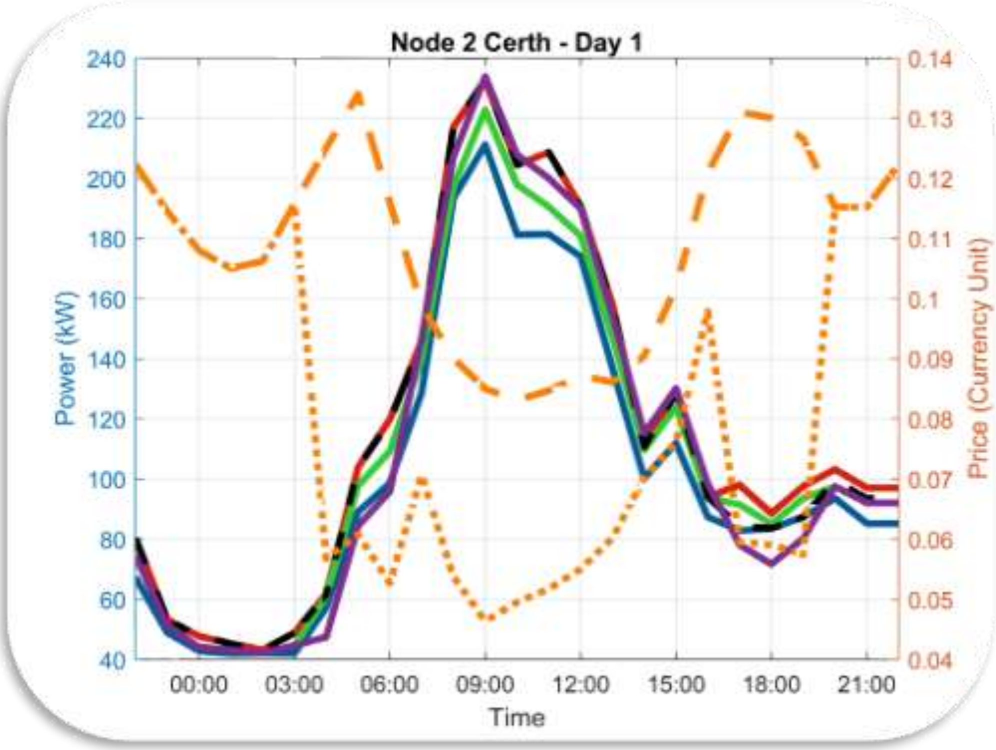

Figure 40. Consumption and pricing signals for Node 2 (CERTH) on Day 1. Down flex bound (blue line); Up flex bound (red line); Baseline (green line); Aggregated decision (dashed black line); DSO desired trajectory (purple line); Retail price tariff (dashed orange line); DSO discounted price (dotted orange line)

When the DSO requests a deviation from the baseline consumption profile (indicated by the purple line), the agent adjusts its aggregated decision (represented by the black dashed line) to meet the grid's requirements, ensuring that the resulting profile remains within the prescribed flexibility bounds (the blue and red lines). In periods without a specific DSO request, the agent is free to optimize energy consumption based on pricing signals, where the standard retail price (dashed orange line) aligns with the discounted price (dotted orange line).

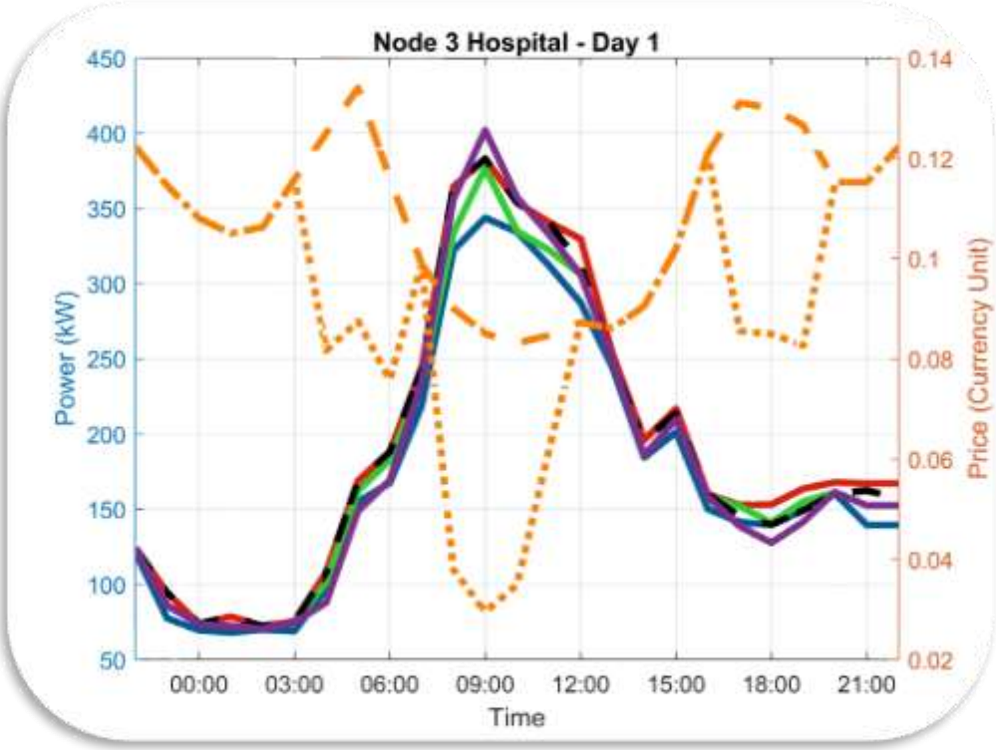

Figure 41. Consumption and pricing signals for Node 3 (Hospital) on Day 1. Down flex bound (blue line); Up flex bound (red line); Baseline (green line); Aggregated decision (dashed black line); DSO desired trajectory (purple line); Retail price tariff (dashed orange line); DSO discounted price (dotted orange line)

Notably, the discounted price applies the full discount only when the entire DSO request is fulfilled; if the request is only partially met, a proportionally reduced discount is provided through linear interpolation to encourage complete compliance. Overall, the agent's aggregated decision consistently remains within the flexibility bounds, confirming that thermal comfort constraints are maintained despite dynamic adjustments in consumption.

Table 2 summarizes the percentage cost differences and percentage residual demand differences for each node on three test days, compared to the baseline scenario.

Table 2. Comparison of percentage cost and residual demand differences relative to the baseline for Node 2 and Node 3.

Node	Day	Percentage Difference Cost (%)	Percentage Difference Residual (%)
Node 2 - Certh	Day 1	9.8	-4.1
	Day 2	8.6	-5.3
	Day 3	12.8	-7.6
Node 3 - Hospital	Day 1	4.9	-3.1
	Day 2	2.1	-3.1
	Day 3	5.6	-5.8

The analysis reveals several key insights regarding the performance of the RL agent. First, the positive percentage values in the “Percentage Difference Cost” column clearly indicate a monetary cost reduction relative to the baseline. Specifically, Node 2 exhibits cost savings ranging from 8.6% to 12.8%, while Node 3 achieves more modest yet still notable savings between 2.1% and 5.6%. In contrast, the “Percentage Difference Residual” values are negative across all test days, implying that the agent’s decisions resulted in a slightly higher total energy consumption compared to the baseline. This increase in consumption is not necessarily a negative outcome; rather, it reflects a strategic shift where energy is consumed during cheaper periods or adjusted to meet DSO requests, rather than an overall inefficiency in energy use. However, in future realizations the agent will be prompted to reduce this percentage gap which may increase more the energy savings and the monetary cost.

Furthermore, the degree of cost savings is closely tied to the incentive policies and the available flexibility of each building. Higher discounts and greater flexibility allow the RL agent to shift demand more aggressively, leading to larger cost reductions. Looking ahead, future project stages will explore different incentive policies, and the agent may be further constrained to maintain the same total daily energy consumption as the baseline. This will provide additional insights into how incentive design interacts with flexibility to shape both cost and consumption outcomes.

In summary, the results underscore several key takeaways. The RL agent demonstrates effective coordination with DSO requests by adjusting consumption profiles in a manner that aligns with grid needs. Even in scenarios where overall consumption increases, the strategic load shifting achieved by the agent results in significant cost reductions, highlighting the economic benefits of an incentive-driven demand response approach. Moreover, the methodology is scalable and holds promise for extension to additional nodes and more complex energy systems, where multiple energy vectors—such as heating, cooling, and electricity—are managed concurrently.

It is important to note that while the pilot results were obtained with each node representing a single building, we also used simulated data to illustrate the functionality of the system at a district level. In the simulated scenario, a district is constituted by three buildings, and the DSO requests are provided at the district level. The agent then produces decisions for each building accordingly, ensuring that the aggregated consumption profile meets the DSO's requirements while still respecting the individual flexibility and thermal comfort constraints of each building. This approach demonstrates the scalability of our solution and its potential applicability in more complex, multi-building district scenarios.

In this scenario, the IS13 tool is tested on a node composed of three distinct buildings, each with its own baseline consumption profile and flexibility bounds. The overall objective remains the same: to sustain thermal comfort within each building while complying with any DSO requests at the district level. Figure 42 depicts the consumption profiles and pricing signals for each individual building, while also the aggregated profile of the total consumption at the node/district level. In each plot, the black dashed line represents the agent's recommended consumption, which seeks to follow the DSO request (purple line) whenever possible and otherwise exploit lower price tariffs (orange dashed and dotted lines). A key observation is that, during the evening hours (approximately 18:00 to midnight), the agent's recommended profile diverges significantly from the purple line. This deviation occurs because, in that time frame, the DSO request effectively aligns with the baseline consumption (indicating no additional requirement for demand shifting). Consequently, the agent is "free" to respond purely to price incentives—shifting consumption to less expensive periods while staying within each building's flexibility bounds.

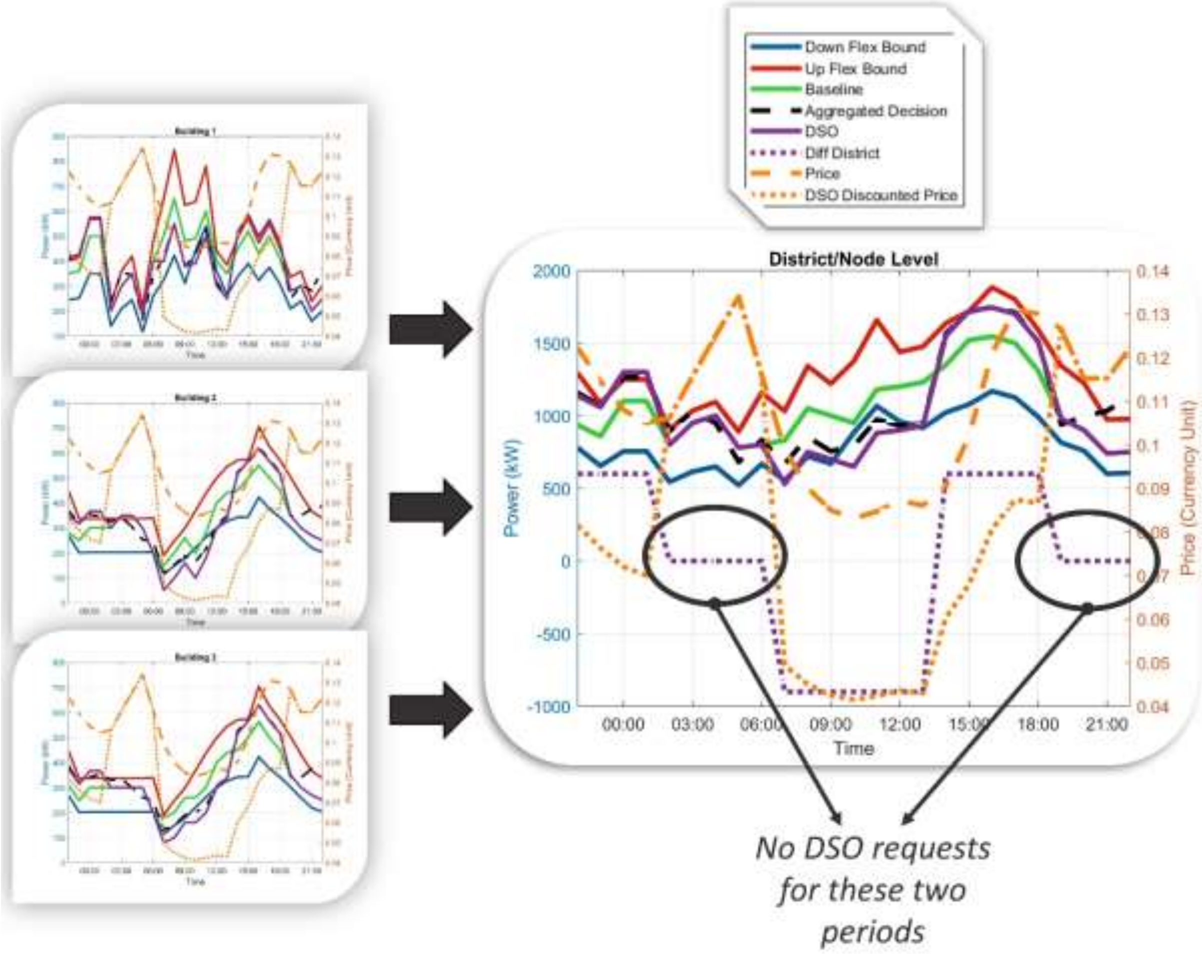

Figure 42. Combined visualization of the three-building node at both the individual-building and aggregated district levels. The left subfigures show each building's baseline (green), flexibility bounds (blue and red), and the RL agent's recommended consumption (black dashed), while the right panel aggregates these profiles to the district level. The purple line indicates the DSO's requested consumption, and the orange lines reflect price signals (with a dotted line representing the discounted price). The circled areas highlight periods with no active DSO request, during which the agent shifts consumption based primarily on price tariffs.

Table 3 provides the percentage difference in cost and residual consumption for each building, while Table 4 summarizes the same metrics at the aggregated district level. The results confirm that the agent's profile consumes more energy overall than the baseline (negative values in the Percentage Difference Residual column), yet yields a cost reduction of approximately 8.8% at the district level. This outcome highlights how strategic load shifting can produce monetary savings even if total consumption increases slightly. Over time, these results could be further refined by encouraging a zero net energy difference to reduce the negative residual values.

It is also worth noting that the agent exhibits performance similar to the Greek pilot case because the same hyperparameters and penalty functions were used in both scenarios. Nonetheless, these findings demonstrate the scalability of the approach: the RL agent can handle situations where a node consists of multiple buildings, each with individual constraints, while still meeting higher-level DSO requirements. Moving forward, additional metrics—such as the percentage of the Aggregated Decision that precisely aligns with the DSO request and a more explicit measure of thermal comfort impact—will be introduced. Preliminary observations, however, indicate that the agent effectively balances grid demands, cost savings, and user comfort at this aggregated district level.

Table 3. Percentage difference in cost and residual consumption for each building in the multi-building node scenario, compared to the baseline.

Building	Percentage Difference Cost (%)	Percentage Difference Residual (%)
1	10.1	-1.6
2	8.2	-5.3
3	8.1	-5.4

Table 4. Aggregated cost and consumption differences at the district level, summarizing the overall performance of the three-building node scenario relative to the baseline.

District	Percentage Difference Cost (%)	Percentage Difference Residual (%)
District Level	8.8	-3.99

3.2.3.4 Next Steps

The following steps are planned to further refine and scale the Aggregated Demand Portfolio Manager:

- Refinement of incentive structures and reward function: Optimize discount policies to ensure that the full discount is applied only when DSO requests are fully met, with linear interpolation used for partial compliance. At the same time, reformulate the reward function to support different policies and better guide the agent's decision-making.

- Zero net energy targeting: Modify reward functions and adjust agent parameters to aim for zero net energy difference over the day, reducing the negative residual consumption values.
- Enhanced performance metrics: Incorporate additional metrics such as the percentage of the aggregated decision aligned with DSO requests and explicit thermal comfort penalties to better quantify performance.
- Scalability and robustness testing: Evaluate the tool's performance in larger, multi-building district scenarios. Also, adjust hyperparameters and penalty functions to handle more complex energy systems.
- Integration of additional pilot data: Expand the evaluation to include data from additional pilot cases, enhancing the robustness of the results. Also, transition from simulated data to real-world pilot data if feasible to validate the system's effectiveness under actual operating conditions.
- Integration with Task 4.6: Collaborate with Task 4.6 to ensure seamless interoperability with other components of the EVELIXIA platform, enhancing overall decision-making and grid management capabilities.

4 CONCLUSIONS

This deliverable reports on the development of the Autonomous District Digital Twin (ADDT) within the EVELIXIA Grid-to-Building (G2B) Services Framework, designed for validating various scenarios at the district level in a virtual testbed. The ADDT expands the Buildings as Active Utility Nodes (BAUNs) concept to entire districts, enabling effective scenario testing, energy profiling, optimized energy management, and maintenance strategies across multiple building nodes and grid networks.

Two primary objectives have guided this deliverable. The first objective involves the development of EVELIXIA's Network Awareness and Forecasting Framework (NAFF), which includes innovative solutions such as Multi-Vector Grids Energy Modelling and Simulation (IS15) – an intelligent Virtual Network (iVN) model facilitating city or community-level energy distribution simulations – and the Multi-Vector Smart Grid Maintenance Service (IS14), enhancing predictive maintenance through asset health monitoring and maintenance optimization simulations.

The second objective addresses the development of EVELIXIA's Autonomous District Decision Support Framework (ANDSF). It comprises the Grid Investment Planning Assistant Service (IS11), supporting strategic long-term planning through proactive identification of future network bottlenecks via comprehensive Cost-Benefit Analysis (CBA); the Multi-Vector Energy Network Manager Service (IS12), offering grid operators solutions for local congestion management through flexibility-driven actions; and the Aggregated Demand Portfolio Manager Service (IS13), facilitating aggregators' active participation in energy balancing markets through demand portfolio optimization.

The outcomes of tasks T4.3 and T4.4 demonstrate potential for applicability across diverse network contexts and operational environments. The developed models and frameworks, through their generalizable structure and adaptability to specific stakeholder needs, underline a solid foundation for replication and scalability.

Moving forward, efforts will be focused holistically on implementing, validating, and integrating all developed services within a cohesive, operational ecosystem. Essential to this integration are structured data exchange processes facilitated through the EVELIXIA Services Broker, ensuring seamless interaction between simulation engines, decision-support services, and real-time data streams. An emphasis will be placed on validation through iterative collaboration with stakeholders such as system operators, aggregators, and utilities, to co-develop scenarios, define operational parameters, and refine tools through real-world insights. Additionally, addressing identified barriers – including data heterogeneity, integration complexity, service interconnections, and operational variability – will be crucial. Continued partners' engagement and access to real mandatory operational data from the networks under study, are necessary to ensure successful implementation, scalability, and adoption of the proposed innovative solutions.

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6 ANNEXES

6.1 Annex 1

Modified IEEE 33-bus test system, adapted for GIPA test-run analysis (Section 3.2.1.3). The configuration is implemented in MATPOWER v8.0 using the following data structures in MATLAB R2024a:

```
function mpc = case33_modified
%CASE33_MODIFIED  Modified 5-bus distribution test system in MATPOWER format

%% MATPOWER Case Format : Version 2
mpc.version = '2';

%% System MVA base
mpc.baseMVA = 100;

%% Bus data
%  [bus_i type Pd Qd Gs Bs area Vm Va baseKV zone Vmax Vmin]
mpc.bus = [
   1  3  0   0   0  0  1  1.0  0  12.66  1  1.05  0.95;  % Slack bus
   2  1  5   2.5  0  0  1  1.0  0  12.66  1  1.05  0.95;  % Medium-sized load center
   3  1  8   4.0  0  0  1  1.0  0  12.66  1  1.05  0.95;  % Industrial/commercial load center
   4  1  3   1.5  0  0  1  1.0  0  12.66  1  1.05  0.95;  % Residential/mixed-use load center
   5  2  0   0   0  0  1  1.0  0  12.66  1  1.05  0.95;  % Renewable energy injection
];

%% Generator data
%  [bus Pg  Qg  Qmax Qmin Vg mBase status Pmax Pmin Pc1 Pc2 Qc1min Qc1max
Qc2min Qc2max ramp_agc ramp_10 ramp_30 ramp_q apf]
mpc.gen = [
   1  0  0  500  -500  1.0 100 1  100  0  0  0  0  0  0  0  10  10  30  0  0;
% Slack bus generator
   5  -10  0  500  -500  1.0 100 1  0  -10 0  0  0  0  0  0  10  10  30  0  0;
% Renewable energy source
];

%% Branch data
%  [fbus tbus r     x     b rateA rateB rateC ratio angle status angmin angmax]
mpc.branch = [
   1  2  0.0922  0.0470  0  100  100  100  0   0   1   -360  360;
   2  3  0.4930  0.2511  0  100  100  100  0   0   1   -360  360;
   3  4  0.3660  0.1864  0  100  100  100  0   0   1   -360  360;
   4  5  0.3811  0.1941  0  100  100  100  0   0   1   -360  360;
];

%% Generator cost data
%  [type startup shutdown n c(n-1) ... c0]
mpc.gencost = [   2  0  0  3  0.02  2.0  0; ];
end
```