Trustworthy AI

Federated Energy



ENERTEF

A Common Federated AI Testing and Experimentation Facility for the European Energy Sector

Secure experimentation · AI living labs · Privacy-preserving validation

EnerTEF: A Common Federated AI Testing and Experimentation Facility for the European Energy Sector

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EnerTEF: A Common Federated AI Testing and Experimentation Facility for the European Energy Sector

Abstract: EnerTEF: A Common Federated AI Testing and Experimentation Facility for the European Energy Sector

The rapid digitalisation of the European energy system demands trustworthy artificial-intelligence (AI) solutions that can be validated under realistic, privacy-preserving conditions before market deployment. This paper introduces EnerTEF, a Europe-wide federated testing and experimentation facility designed to bridge the gap between AI development and operational use in the energy domain. We first outline the motivation for a dedicated infrastructure, linking the initiative to the European Commission's push for a Common European Energy Data Space and the growing need for reliable AI in renewable-energy, grid, building, community, storage, and e-mobility applications. A review of existing AI testing platforms and federated learning frameworks highlights their limitations regarding cross-border data governance, domain coverage, and collaborative model development, positioning EnerTEF as a novel solution.

The conceptual architecture comprises five core nodes and three satellite sites interconnected through secure communication layers and orchestrated by a central hub that manages experiment lifecycles. Within this framework, "AI Living Labs" enable energy stakeholders, AI developers, and consulting firms to co-create adaptive models, share requirements, and iteratively refine prototypes in controlled yet realistic environments. GDPR-compliant data handling, secure multi-party computation, differential privacy, and explicit ethical guidelines ensure that model training and evaluation respect privacy and societal values.

Implementation details of the RWTH node and the additional core and satellite nodes illustrate the infrastructure's scalability and domain-specific integration with local operators. Representative pilots - grid-balancing for distribution system operators, predictive maintenance of storage assets, and e-mobility demand forecasting - demonstrate how EnerTEF accelerates AI validation, improves performance, and enhances stakeholder confidence. An evaluation methodology based on performance, scalability, privacy guarantees, and user satisfaction is applied, revealing significant gains in model trustworthiness and deployment readiness.

The discussion reflects on strengths, challenges, and lessons learned, particularly regarding interoperability and stakeholder engagement. Finally, a roadmap for future extensions - including additional satellites, deeper integration with the European Energy Data Space, and support for emerging AI paradigms - outlines the path toward a continent-wide service. EnerTEF thus provides a robust, collaborative, and ethically grounded platform that advances trustworthy AI for Europe's energy transition.

1. Introduction

1.1 Motivation: The Emerging Need for Trustworthy AI in Energy

The European energy sector is undergoing a rapid transformation driven by decarbonisation, digitalisation, and the integration of renewable energy sources (RES). These trends generate unprecedented volumes of heterogeneous data - from smart-meter readings to grid-level forecasts - creating fertile ground for artificial intelligence (AI) to optimise operations, improve reliability, and enable new services such as demand-response and predictive maintenance.

However, the stakes are high: AI-driven decisions affect grid stability, consumer costs, and the overall resilience of the energy transition. Consequently, regulators, system operators, and market participants are demanding **trustworthy AI** - systems that are transparent, robust, secure, and compliant with ethical and legal standards. The lack of a common, Europe-wide environment to test, validate, and certify such AI solutions has become a critical bottleneck.

1.2 Rising Demand for Trustworthy AI

Recent policy documents (e.g., the European Commission's "AI Act" and the "Digital Europe Programme") explicitly call for **trustworthiness by design** in high-impact sectors, including energy. Stakeholders report three converging pressures:

1. **Regulatory compliance** - GDPR, the forthcoming AI Act, and sector-specific standards require demonstrable data protection and algorithmic accountability.

2. **Operational reliability** - Grid operators need guarantees that AI models will not introduce instability under extreme conditions.

3. **Market confidence** - Investors and consumers are more likely to adopt AI-enabled services when they can verify performance and ethical compliance.

These pressures translate into a market need for a shared testing ground where AI models can be evaluated against realistic, yet controlled, energy-system scenarios while respecting data sovereignty.

1.3 The Development-Deployment Gap

Despite a vibrant ecosystem of AI research labs and start-ups, a **significant gap** persists between prototype development and real-world deployment:

- **Data silos** - Energy data are often owned by utilities, transmission system operators (TSOs), or municipalities, limiting access for external AI developers.

- **Heterogeneous infrastructures** - Variations in grid topology, market rules, and ICT stacks make it difficult to transfer models from one context to another.

- **Lack of standardized evaluation** - Existing AI testing platforms are either domain-specific (e.g., smart-building simulators) or proprietary, offering no common metrics for trustworthiness across the sector.

Consequently, many promising AI solutions stall at the proof-of-concept stage, never reaching the market where they could deliver carbon-reduction benefits.

1.4 Alignment with European Commission Initiatives

EnerTEF is deliberately positioned to **bridge** this gap and to align with key European Commission initiatives:

- **Common European Energy Data Space (CEEDS)** - By adopting CEEDS's data-sharing principles, EnerTEF enables federated access to high-quality, GDPR-compliant datasets while preserving data ownership.

- **European AI Strategy** - The facility implements the "trustworthy AI" pillars (explainability, robustness, privacy) through built-in testing modules, thereby supporting the Commission's goal of fostering

AI that respects European values.

- **Digital Twin and Smart Grid Policies** - EnerTEF's federated architecture integrates digital-twin models of distribution and transmission networks, providing a sandbox that complies with the EU's Smart Grid and Digital Twin roadmaps.

Through these alignments, EnerTEF not only responds to current policy demands but also creates a reusable, scalable infrastructure that can evolve alongside future European regulatory frameworks.

1.5 Scope of the Introduction

The remainder of this publication builds on the motivation outlined above. **Section 2** reviews existing AI testing infrastructures and highlights why a Europe-wide solution is required. **Section 3** details the conceptual architecture of EnerTEF, while **Section 4** introduces the AI Living Labs that operationalise collaborative model development. Subsequent sections address privacy, implementation, pilot use cases, evaluation results, and the roadmap for extending the facility continent-wide.

2. Background and Related Work

2.1 AI Testing Infrastructures

A broad spectrum of AI testing environments has emerged over the past decade, ranging from generic machine-learning pipelines (e.g., **MLflow**, **Kubeflow**) to domain-specific simulators such as **GridLAB-D**, **OpenDSS**, and the **Power System Toolbox**. These platforms excel at rapid prototyping and reproducible experimentation, yet they share several shortcomings when applied to the European energy sector:

Platform	Strengths	Limitations for Energy-AI
MLflow / Kubeflow	End-to-end experiment tracking, model registry, CI/CD integration	No built-in support for high-fidelity power-system models; assumes centralized data storage, which conflicts with GDPR and data-ownership constraints.
GridLAB-D, OpenDSS	Detailed distribution-grid physics, open-source, extensible	Primarily simulation-only; lacks mechanisms for federated data ingestion, multi-stakeholder access control, and systematic performance benchmarking across heterogeneous operators.
AI4EU Sandbox	European-wide AI resources, collaborative notebooks	Focuses on generic AI workloads; does not provide energy-sector-specific testbeds (e.g., renewable-generation forecasts, demand-response scenarios) nor a federated governance model.
NIST AI Testbed (US)	Standardised AI evaluation metrics, reproducibility	Geographically limited to the United States; does not address EU-specific regulatory frameworks (GDPR, CE-Marking) or the Common European Energy Data Space.

Collectively, these infrastructures demonstrate the feasibility of AI testing but fall short of delivering a **sector-wide, privacy-preserving, and policy-aligned environment** that can be used by multiple European energy actors simultaneously.

2.2 Federated Learning Frameworks

Federated learning (FL) has become the de-facto approach for training models without moving raw data. The most widely adopted frameworks include:

- **TensorFlow Federated (TFF)** - research-oriented API, strong integration with TensorFlow ecosystem.
- **Flower** - lightweight, language-agnostic orchestration, supports heterogeneous clients.
- **PySyft / OpenMined** - focuses on secure multi-party computation (SMPC) and differential privacy.
- **FedML** - provides a unified interface for cross-device and cross-silo FL, with built-in support for compression and personalization.

While technically mature, these frameworks exhibit three critical gaps for the European energy context:

1. **Regulatory Alignment** - Most FL toolkits assume a generic data-privacy model; they do not embed EU-specific GDPR compliance checks (e.g., data-subject rights handling, lawful basis documentation) required for DSO-level datasets.
2. **Domain Heterogeneity** - Energy data span time-series from smart meters, SCADA streams, weather forecasts, and market bids, each with distinct sampling rates and quality constraints. Existing FL libraries lack native adapters for such heterogeneous time-series pipelines, forcing developers to implement costly custom preprocessing layers.
3. **Scalable Orchestration Across Nations** - Energy operators are organized in national or regional clusters with distinct network topologies and latency profiles. Current FL orchestration layers (central server or hierarchical topologies) are not designed to respect cross-border data-sovereignty rules or to interoperate with the **Common European Energy Data Space** envisioned in the Introduction.

Consequently, while FL frameworks provide the algorithmic backbone for privacy-preserving training, they do not constitute a **complete testing and experimentation facility** for the energy sector.

2.3 Energy-Sector Data Platforms

European energy stakeholders already operate several data platforms that expose grid, market, and renewable-generation information:

Platform	Scope	Main Constraints
ENTSO-E Transparency Platform	Continental transmission-system data, market results	Data are aggregated and published with a delay; raw high-frequency measurements remain siloed within national TSOs.
Open Power System Data (OPSD)	Open datasets for research (load, generation, weather)	Static snapshots; no live-streaming or API for real-time model validation.
National DSO Portals (e.g., Germany's BNetzA, France's RTE)	Grid-operation data, outage information	Access governed by national regulations; often requires bespoke contracts and does not support federated query execution.
European Data Space Initiatives	Emerging cross-border data-exchange framework	Still under definition; current prototypes lack built-in AI-testing hooks, provenance tracking, and automated compliance checks.

The common thread across these platforms is **data silos**: ownership remains with the operator, and sharing is limited to aggregated or anonymised extracts. Moreover, none of the platforms provide a **standardised, reproducible environment** where AI models can be benchmarked against live operational data while guaranteeing GDPR-compliant handling of personal or commercially sensitive information.

2.4 Synthesis of Gaps and Positioning of EnerTEF

The review above highlights a **triad of unmet needs**:

1. **End-to-end, sector-specific testing** that couples high-fidelity power-system simulators with live operational streams.

2. **Federated learning orchestration** that respects EU data-sovereignty, provides built-in GDPR tooling, and can handle the heterogeneity of energy time-series.

3. **Pan-European data-access layer** aligned with the **Common European Energy Data Space**, enabling cross-border collaboration without compromising proprietary or personal data.

EnerTEF is deliberately engineered to fill these gaps:

- **Federated Architecture (Section 3)** - Five core nodes (including the RWTH hub) and three satellite sites form a continent-wide federation, each retaining full data ownership while participating in joint experiments through a **central orchestration hub**.

- **Living-Lab Integration (Section 4)** - The facility embeds AI Living Labs that provide realistic, controllable environments for model validation, directly addressing the development-deployment gap identified in the Introduction.

- **GDPR-by-Design Stack (Section 5)** - EnerTEF incorporates differential privacy, secure multi-party computation, and automated compliance reporting, ensuring that every federated experiment meets European legal standards.

- **Standardised Benchmark Suite** - Building on the limitations of existing testbeds, EnerTEF offers a curated set of energy-sector benchmarks (grid balancing, storage maintenance, e-mobility forecasting) with reproducible metrics, facilitating trustworthy AI assessment across all participating actors.

In summary, while current AI testing infrastructures, FL frameworks, and energy data platforms each contribute valuable building blocks, none delivers the **holistic, Europe-wide, policy-compliant testing ecosystem** required for trustworthy AI in the energy transition. EnerTEF therefore represents a **novel, integrative solution** that unifies these components under a common governance model, directly responding to the challenges outlined in the Introduction and setting the stage for the detailed architecture, pilots, and evaluation presented in the subsequent sections.

3. Conceptual Architecture of EnerTEF

3.1 Overview of the Federated Landscape

EnerTEF is conceived as a **Europe-wide federated testing fabric** that interconnects a set of autonomous yet coordinated computing sites. The federation is deliberately **de-centralised** to preserve data sovereignty (see Section 5 "Data Privacy, Security, and Ethical Compliance") while still offering a **single logical view** for experiment designers. At the heart of this landscape lies a **central orchestration hub** that mediates experiment lifecycle management, resource discovery, and policy enforcement without ever holding raw energy data.

3.2 Core Nodes - The Backbone of the Facility

The architecture comprises **five core nodes**, each hosted by a major research or operational partner and responsible for a distinct domain of the energy ecosystem:

Core Node	Host Institution / Partner	Primary Domain Coverage	Key Capabilities
Node A	RWTH Aachen University	Renewable Energy Sources (wind, solar, hydro)	High-fidelity generation simulators, weather-data ingestion pipelines
Node B	European Distribution System Operator (DSO) Alliance	Power-grid operation & balancing	Real-time grid state estimation, contingency analysis
Node C	Building Energy Research Centre (BERC)	Buildings & Communities	Digital twins of residential/commercial clusters, demand-response models
Node D	Storage & Flexibility Consortium	Energy storage & flexibility services	Battery-system emulators, market-participation APIs
Node E	e-Mobility Innovation Hub	Electric-vehicle charging & mobility	Mobility-as-a-service (MaaS) demand generators, charger-network simulators

Each core node runs a **local execution environment** (container-orchestrated Kubernetes clusters) that hosts both **simulation engines** (e.g., GridLAB-D, OpenDSS) and **federated learning workers** (TensorFlow Federated, Flower). The nodes expose **standardised service interfaces** (REST + gRPC) that the orchestration hub can invoke, while all data remains behind the node's firewall.

3.3 Satellite Sites - Extending Reach and Diversity

To capture **regional heterogeneity** and to involve smaller operators, three **satellite sites** are attached to the federation:

1. **Satellite S1 - Nordic Testbed** - Focus on high-latitude renewable integration and cross-border grid coupling.

2. **Satellite S2 - Mediterranean Pilot** - Emphasises solar-dominated generation and demand-side flexibility in densely populated urban districts.

3. **Satellite S3 - Central-East European Hub** - Provides access to legacy distribution networks and emerging e-mobility corridors.

Satellites differ from core nodes in that they **do not host a full orchestration stack**; instead, they contribute **domain-specific datasets** and **scenario generators** that are pulled on-demand by the central hub. Their lightweight footprint enables rapid onboarding of new partners while still complying with the GDPR-by-design principles outlined in Section 5.

3.4 Communication Layers - Secure, Scalable Inter-Node Connectivity

EnerTEF's communication fabric is organised in three logical layers:

Layer	Purpose	Technologies
Control Plane	Experiment registration, resource discovery, policy dissemination	**gRPC** with mutual TLS, **OPA** (Open Policy Agent) for fine-grained access control
Data Plane	Transfer of model parameters, encrypted gradients, and provenance metadata	**Secure Multi-Party Computation (SMPC)** channels, **TLS 1.3**, optional **QUIC** for low-latency streaming
Monitoring & Telemetry	Real-time health checks, performance metrics, audit logs	**Prometheus** + **Grafana**, **Elastic Stack** for immutable audit trails (required for compliance verification)

All layers are **policy-aware**: before any payload traverses the data plane, the orchestration hub validates the request against the **EU-wide governance model** (see Section 5) and the **experiment's consent artefacts**.

3.5 Central Orchestration Hub - The Experiment Management Engine

The **central orchestration hub** is the "brain" of EnerTEF. Its responsibilities include:

1. **Experiment Lifecycle Management** - From proposal submission (via a web portal) to scheduling, execution, and result archival.

2. **Resource Allocation & Scheduling** - A multi-objective scheduler balances compute capacity, network bandwidth, and data-locality constraints across the five core nodes.

3. **Policy Enforcement & Auditing** - Integrates with the **policy engine** (OPA) to ensure every step respects GDPR, CE-Marking, and sector-specific regulations.

4. **Result Federation** - Aggregates model artefacts, performance metrics, and provenance records, then publishes them to the **EnerTEF Knowledge Base** (a FAIR-compliant data lake).

5. **User Collaboration Services** - Provides role-based workspaces, versioned notebooks, and a **Living-Lab API** that connects to Section 4's collaborative model environment.

The hub itself is **stateless** with respect to raw energy data; it only stores **metadata** and **encrypted model updates**. This design guarantees that the hub cannot become a single point of failure for data confidentiality, aligning with the privacy guarantees highlighted in Section 5.

3.6 Interaction Flow - From Experiment Definition to Execution

A typical end-to-end flow proceeds as follows:

1. **Experiment Definition** - An AI developer drafts a scenario (e.g., "grid-balancing with federated demand forecasts") in the EnerTEF portal.

2. **Policy Check** - The hub invokes the policy engine; consent forms and data-usage contracts are verified.

3. **Resource Negotiation** - The scheduler queries the **resource catalogue** of each core node and selects the optimal subset (e.g., Node B for grid simulation, Node C for demand profiles).

4. **Secure Deployment** - Container images are pushed to the selected nodes via **signed OCI artifacts**; SMPC channels are established for gradient exchange.

5. **Execution & Monitoring** - Nodes run the simulation and federated learning loops, streaming telemetry to the monitoring layer.

6. **Result Consolidation** - Upon completion, encrypted model updates are sent back to the hub, decrypted under the consent policy, and stored in the Knowledge Base.

7. **Feedback Loop** - Stakeholders in the AI Living Labs (Section 4) review the outcomes, iterate on model hyper-parameters, and re-submit new experiment cycles.

3.7 Alignment with EU Policy and the Common European Energy Data Space

The architecture is deliberately **aligned with the Common European Energy Data Space (CEEDS)**:

- **Interoperability** - All interfaces adopt the **EU-wide Energy Data Exchange (EDE) schema**, enabling seamless data discovery across national borders.

- **Data Sovereignty** - By keeping raw datasets inside the jurisdiction of the owning node, EnerTEF respects the CEEDS principle of "data stays where it is generated".

- **Regulatory Traceability** - Every experiment is logged with a **digital twin of the consent chain**, satisfying both GDPR and the upcoming **EU AI Act** requirements.

Through this tightly coupled yet loosely coupled federation, EnerTEF delivers a **scalable, secure, and policy-compliant environment** that can evolve as new AI paradigms and energy market actors join the European energy transition.

4. AI Living Labs and Collaborative Model

4.1 Definition and Objectives of AI Living Labs

The **AI Living Lab** is a purpose-built, sandbox-style environment that sits on top of the federated fabric described in **Section 3**. Its primary purpose is to bring together three complementary actor groups - energy-sector stakeholders (DSOs, TSOs, producers, aggregators), AI developers (research labs, start-ups, large-scale vendors), and consulting / system-integration firms - and enable them to **co-create, test, and refine adaptive AI models** under conditions that are both **controlled** (strict policy enforcement, reproducible experiment definition) and **realistic** (live or high-fidelity synthetic energy data, domain-specific simulation engines).

Key objectives are:

1. **Accelerate the translation** of AI research prototypes into market-ready solutions for the European energy sector.

2. **Close the development-deployment gap** identified in the Introduction (Section 1) by providing a shared, policy-compliant experimentation space.

3. **Foster continuous learning** through iterative feedback loops that incorporate stakeholder-driven requirements and operational constraints.

4. **Ensure trustworthiness** by embedding GDPR-by-design, EU AI-Act compliance, and ethical guidelines (see Section 5) directly into the lab workflow.

4.2 Stakeholder Roles and Collaborative Workflow

Actor	Core Responsibilities	Value Added
Energy Stakeholders (DSOs, TSOs, producers, aggregators)	Provide domain expertise, operational constraints, and access to (real or synthetic) data streams via the federation nodes.	Ground truth for model relevance; guarantee that prototypes respect grid codes and market rules.
AI Developers (research groups, start-ups, vendors)	Design model architectures, implement training pipelines, and deliver prototype code packages.	Bring cutting-edge algorithms and AI expertise to the energy context.
Consulting / System-Integration Firms	Translate stakeholder requirements into formal experiment specifications, orchestrate resource allocation, and mediate IP and licensing discussions.	Bridge the gap between technical AI work and business/regulatory needs; ensure smooth hand-over to operators.

The **collaborative workflow** follows a six-step cycle (illustrated in Figure 4.1 of the full report):

1. **Requirement Capture** - Stakeholders articulate use-case goals, performance KPIs, and regulatory constraints in a structured template.

2. **Experiment Blueprint** - Consulting partners convert the template into a *Living Lab experiment definition* (model code, data access profile, simulation scenario).

3. **Policy & Privacy Check** - The central orchestration hub (Section 3) validates the blueprint against GDPR, EU AI-Act, and node-specific OPA policies.

4. **Secure Deployment** - Federated workers are instantiated on the relevant core nodes; data remains local, and only model updates or encrypted aggregates cross the data plane.

5. **Iterative Evaluation** - Results are visualised in the lab dashboard; stakeholders provide feedback on accuracy, robustness, and operational feasibility.

6. **Model Adaptation** - Developers refine the model (hyper-parameters, architecture, training strategy) and the cycle repeats until the agreed acceptance criteria are met.

4.3 Adaptive Model Co-Creation Process

AI Living Labs promote **adaptive models** - systems that can evolve as new data, regulations, or market conditions emerge. The co-creation process embeds three technical mechanisms:

1. **Federated Continuous Learning (FCL)** - Leveraging the federated learning stack (TensorFlow Federated, Flower, etc.) described in the background (Section 2), model weights are updated locally on each core node and aggregated centrally using secure multi-party computation (SMPC) to preserve privacy.

2. **Scenario-Driven Simulation Hooks** - High-fidelity simulators (e.g., GridLAB-D for grid dynamics, EnergyPlus for building loads) are coupled to the training loop, allowing developers to test model behaviour under *what-if* conditions (e.g., extreme weather, market price spikes).

3. **Dynamic KPI Re-weighting** - The lab dashboard lets stakeholders adjust the relative importance of KPIs (e.g., forecast RMSE vs. CO reduction) on-the-fly; the orchestration hub re-optimises the loss function accordingly, producing a model that aligns with evolving business priorities.

Through these mechanisms, a prototype that initially targets "day-ahead load forecasting" can seamlessly evolve into a **multi-objective predictor** that also supports ancillary service bidding, without leaving the Living Lab environment.

4.4 Living Lab Infrastructure within EnerTEF

The Living Lab is realised as a **service layer** on top of the federated architecture (Section 3). Its main components are:

- **Experiment Definition Portal** - Web-based UI where stakeholders author JSON-based experiment manifests (data sources, simulation models, policy tags).

- **Orchestration Adapter** - Middleware that translates manifests into Kubernetes-style job specifications for the core nodes, invoking the central hub's resource-negotiation API.

- **Secure Data Access Gateway** - Enforces node-local data stay-local policies; provides encrypted feature streams to the federated learning workers via the Data Plane (TLS 1.3, optional QUIC).

- **Result Federation Engine** - Collects model updates, performance metrics, and provenance logs; applies differential-privacy noise where required (see Section 5).

- **Collaborative Dashboard** - Real-time visualisation of training curves, simulation outcomes, and stakeholder feedback; supports role-based access control (RBAC).

All components are containerised and deployed via the same CI/CD pipeline that powers the core nodes, ensuring **consistent versioning** and **traceability** across the federation.

4.5 Governance, Intellectual Property, and Data Sharing

Living Labs operate under a **multi-party governance model** that balances openness with protection of proprietary assets:

- **Policy Contracts** - Each experiment is bound by a machine-readable contract (OPA policy) that specifies permissible data accesses, retention periods, and result-use clauses.

- **IP Attribution Ledger** - A blockchain-based ledger records contributions (code commits, data annotations, model improvements) and automatically generates royalty or licensing statements when a model graduates to production.

- **Data Sharing Agreements** - Stakeholders sign a GDPR-compliant Data Processing Agreement (DPA) that defines the *data-stay-local* principle; only model updates or anonymised aggregates are exchanged, in line with the privacy guarantees outlined in Section 5.

These mechanisms ensure that **trust** - a central theme of the Introduction (Section 1) - is embedded not only technically but also legally and organisationally.

4.6 Integration with the Federated Architecture (Link to Section 3)

The Living Lab does **not** constitute a separate silo; it is a **logical overlay** that re-uses the federation's three communication layers:

- **Control Plane** - Experiment manifests are transmitted via gRPC + TLS to the central hub, where OPA evaluates policy compliance before any resources are allocated.
- **Data Plane** - Local data never leaves the node; model updates travel through SMPC channels, guaranteeing that raw measurements remain under the data owner's control.
- **Monitoring/Telemetry** - Prometheus scrapes performance metrics from each worker, while the Elastic Stack stores provenance logs for auditability (required by the EU AI Act).

By leveraging the same orchestration primitives, Living Labs inherit the **scalability** and **inter-operability** guarantees of the core architecture, enabling pilots to be launched simultaneously across the five core nodes and three satellite sites.

4.7 Illustrative Example: Distributed Grid-Balancing Pilot (Reference to Section 7)

To demonstrate the Living Lab in action, consider the **grid-balancing pilot** described in Section 7:

1. **Stakeholder Input** - A DSO specifies a need for a short-term forecast of net-load variability to optimise battery dispatch.
2. **Blueprint Creation** - A consulting firm encodes the requirement as an experiment manifest that pulls real-time SCADA data from the *Grid* node, couples it with a stochastic renewable generation model from the *Renewables* node, and defines a reinforcement-learning controller as the target AI.
3. **Policy Check** - OPA validates that the DSO's data usage complies with GDPR and the EU AI Act; the experiment is approved.
4. **Federated Training** - The RL agent is trained locally on the Grid and Renewables nodes; updates are aggregated using SMPC.
5. **Iterative Feedback** - The DSO reviews performance dashboards, adjusts the cost-function weighting to penalise over-charging of storage, and re-triggers the training loop.
6. **Graduation** - After meeting the predefined KPI thresholds, the model is exported to the DSO's production environment, with IP and licensing recorded in the attribution ledger.

This end-to-end flow showcases how AI Living Labs **compress months of traditional development** into a few iterative cycles, while preserving data sovereignty and regulatory compliance.

4.8 Summary

AI Living Labs constitute the **collaborative heart** of EnerTEF. By providing a structured, policy-driven, and technically robust environment for co-creation, they transform fragmented AI research into **adaptive, trustworthy solutions** ready for deployment across Europe's heterogeneous energy landscape. The labs build directly on the federated architecture (Section 3) and respect the privacy, security, and ethical standards detailed in Section 5, thereby delivering on the strategic vision outlined in the Introduction (Section 1).

5. Data Privacy, Security, and Ethical Compliance

5.1 GDPR-Compliant Data Handling

Aspect	Mechanism in EnerTEF	Reference
Data-stay-local principle	All raw measurements (e.g., SCADA, smart-meter time-series) remain on the originating **core node** (Section 3) and are never copied to the central orchestration hub.	Section 3 - "central orchestration hub remains stateless with respect to raw energy data."
Legal basis & consent	Each node signs a **Data Processing Agreement (DPA)** that enumerates the lawful basis (contract, legitimate interest, or explicit consent) for every data category. Consent flags are stored in a **policy-metadata registry** that OPA (Open Policy Agent) consults before any experiment is launched.	Section 4 - "OPA-based policy contracts embed trust, legal clarity, and data-ownership protection."
Purpose limitation & minimisation	Experiment designers must declare a **purpose profile** (e.g., load forecasting, fault detection). The orchestration hub automatically trims the data view to the minimal set of attributes required for the declared purpose, using schema-level **attribute-level access control**.	Section 3 - "policy check → resource negotiation → secure deployment."
Pseudonymisation & encryption	Before any data leaves the node's secure enclave, identifiers are replaced by **cryptographic pseudonyms**. All outbound payloads travel over the **Data Plane** encrypted with TLS 1.3 (or QUIC where latency-critical).	Section 3 - "Data Plane (SMPC, TLS 1.3, optional QUIC)."
Right to access, rectification & erasure	A **self-service portal** (part of the Living Lab UI, Section 4) lets data subjects request view, correction, or deletion of their records. Requests trigger a **distributed revocation workflow** that propagates to every node holding derived artefacts (model updates, logs).	Section 4 - "collaborative dashboard ensures traceability and reproducibility."
Data-protection impact assessment (DPIA)	Prior to onboarding a new data source, a **template-driven DPIA** is executed. The outcome is stored in an immutable ledger (see §5.5) and must be approved by the **EU-wide Ethics Board** before the node can participate in federated experiments.	Section 4 - "blockchain-backed IP attribution ledger."

These controls collectively satisfy the **GDPR-by-design and by-default** requirements highlighted in the Introduction (trustworthy AI, regulatory alignment).

5.2 Secure Multi-Party Computation (SMPC)

1. **Protocol stack** - EnerTEF adopts a hybrid SMPC suite:
   - **Additive secret sharing** for high-throughput linear operations (e.g., gradient aggregation).
   - **SPDZ/ABY** for non-linear functions (e.g., activation layers, secure inference).
   - **Homomorphic encryption (HE)** as an optional fallback for ultra-sensitive attributes.
2. **Integration with the Data Plane** -
   - SMPC sessions are instantiated as **gRPC-based services** protected by TLS 1.3.
   - Each node runs a **local SMPC worker** inside a hardened container; the worker receives only **shares** of the data, never the clear values.
3. **Resource negotiation** - When an experiment is submitted, the central orchestration hub performs a **SMPC capability discovery** (CPU, GPU, network latency) across the five core nodes. The hub then composes a **secure computation graph** that respects the latency budgets of the selected satellite sites (Section 3).
4. **Fault tolerance & abort handling** - EnerTEF implements **verifiable secret sharing** and **MAC-based consistency checks**. If a node drops out, the protocol automatically reconstructs the missing shares from the remaining participants, preserving both privacy and continuity.
5. **Auditability** - Every SMPC round logs **commit-hashes of the code**, **input share hashes**, and **output share hashes** to the immutable audit ledger (see §5.5). This enables post-hoc verification without exposing raw data.

5.3 Differential Privacy (DP) Guarantees

DP Component	Implementation in EnerTEF	Rationale
Noise injection	Laplace or Gaussian noise is added **locally** to model updates before they are secret-shared for SMPC aggregation. The noise scale is derived from a **per-node privacy budget (,)** negotiated during the policy-check phase.	Guarantees that a single participant's contribution cannot be reverse-engineered from the aggregated model.

DP Component	Implementation in EnerTEF	Rationale
Privacy-budget accounting	Each node runs a **Renyi DP accountant** that tracks cumulative consumption across experiments. When the budget is exhausted, the node must **re-initialise** its local dataset or obtain fresh consent.	Aligns with GDPR's "data minimisation" and the EU AI Act's risk-management provisions.
Adaptive budgeting	For high-impact pilots (e.g., grid-balancing in Section 7), the budget can be **dynamically re-allocated** based on stakeholder risk assessments performed in the Living Lab (Section 4).	Provides flexibility while preserving overall privacy guarantees.
Post-processing immunity	Since DP is applied **before** any SMPC or model-fusion step, downstream processing (e.g., hyper-parameter tuning) does not degrade the privacy guarantee.	Ensures end-to-end privacy compliance.

The DP layer works hand-in-hand with SMPC: noisy, secret-shared updates are aggregated without ever revealing the underlying raw values, delivering **both cryptographic and statistical privacy**.

5.4 Ethical Governance Framework

1. **Ethics Board & AI Act Alignment** - A **pan-European Ethics Board** (comprising regulator representatives, consumer NGOs, and academic ethicists) reviews every new use-case against the **EU AI Act** risk categories (unacceptable, high-risk, limited-risk, minimal-risk). High-risk AI (e.g., automated demand-response that can affect grid stability) must pass a **pre-deployment conformity assessment**.
2. **Human-in-the-Loop (HITL) safeguards** - For any model that will trigger operational actions (e.g., load shedding), the Living Lab workflow mandates a **human-approval checkpoint** after the model's performance metrics are evaluated but before the model is pushed to the production control system.
3. **Fairness & Bias Audits** -
   - **Statistical parity checks** are run on model outputs per stakeholder group (e.g., residential vs. commercial customers).
   - **Counterfactual analysis** is performed on a synthetic dataset generated within the secure sandbox to detect hidden biases.
4. **Transparency & Explainability** - All federated models are required to expose **model cards** (per the EU AI Trustworthy AI guidelines) that document: data provenance, training configuration, privacy parameters, and known limitations. Explainability tools (SHAP, LIME) are executed **inside the node** and only aggregated explanations are shared with the central hub.
5. **Stakeholder Participation** - The Living Lab's **requirement-capture step** (Section 4) includes an **ethical impact questionnaire** that operators, citizens, and third-party consultants fill out. Answers feed directly into the OPA policy engine, influencing experiment approval.
6. **IP & Attribution** - The **blockchain-backed IP ledger** records the contribution of each participant (data, algorithmic tweaks, domain expertise). This ledger is also used to enforce **fair-share revenue models** for commercial deployments, ensuring that ethical considerations extend to economic fairness.

5.5 Auditing, Monitoring, and Accountability

- **Immutable Audit Ledger** - Every experiment lifecycle event (policy check, DPA signing, SMPC session start, DP budget consumption, model export) is recorded as a **hash-linked transaction** on a permissioned blockchain. The ledger is publicly readable by all federation members, guaranteeing **non-repudiation**.
- **Telemetry Stack** - Leveraging the **Monitoring/Telemetry layer** (Prometheus + Elastic Stack) defined in Section 3, each node streams anonymised performance metrics (CPU, latency, privacy-budget usage) to a **central observability dashboard**. No raw energy data is ever transmitted.
- **Compliance Dashboards** - The Living Lab portal provides **real-time compliance views**: GDPR status, AI-Act risk level, privacy-budget remaining, and ethical-impact scores. Alerts are generated automatically when thresholds are breached (e.g., exceeds the agreed limit).
- **Third-Party Audits** - Independent auditors can request **read-only access** to the audit ledger and telemetry logs. Because raw data never leaves the node, auditors can verify compliance without compromising confidentiality.

- **Incident Response** - In the event of a suspected data breach, the **policy engine** triggers an automated containment workflow: halting all SMPC sessions, revoking pseudonymisation keys, and notifying the Ethics Board. A forensic snapshot of the ledger is then archived for regulatory reporting.

5.6 Summary of Guarantees

Guarantee	Technical Realisation	Policy / Ethical Layer
Data sovereignty	Data-stay-local, encrypted transport, OPA-enforced DP	DPA, GDPR-by-design
Confidential computation	SMPC + TLS 1.3 / QUIC	Central orchestration hub statelessness
Statistical privacy	Local DP noise, budget accounting	EU AI Act risk assessment
Ethical compliance	Ethics Board review, HITL, fairness audits	Living Lab stakeholder questionnaire
Traceability & accountability	Immutable blockchain ledger, telemetry dashboards	OPA contracts, IP attribution ledger

Together, these mechanisms ensure that every AI experiment conducted on EnerTEF respects **GDPR**, delivers **cryptographic and statistical privacy**, and adheres to a **robust ethical framework** - fulfilling the trust and regulatory alignment goals set out in the Introduction (Section 1) and the architectural vision of Section 3.

6. Node and Satellite Implementation

6.1 RWTH Aachen Node - The Anchor of the Federation

The RWTH node, hosted at the Institute for Energy-Efficient Buildings and Smart Grids (IEB-SG) of RWTH Aachen University, serves as the **reference implementation** for the EnerTEF federation. Its design follows the architectural blueprint defined in **Section 3** and demonstrates the full stack of privacy-preserving, GDPR-by-design services.

Component	Technology / Tooling	Role in the Node
Compute & Orchestration	Kubernetes (v1.28) with Kube-Fed for multi-cluster federation, Helm-managed charts for AI services	Provides elastic container execution for simulation engines, federated-learning workers, and model-serving APIs.
Simulation Engines	GridLAB-D 8.0, OpenDSS 0.9, EnergyPlus 9.6, PyPSA 0.23	Enables high-fidelity modelling of **renewables, distribution grids, building envelopes, storage assets, and e-mobility charging infrastructure**.
Data-Plane Security	Hybrid SMPC stack (ABY + SPDZ), TLS 1.3, optional QUIC, OPA policy enforcement	Guarantees that raw time-series data (e.g., SCADA, smart-meter, PV inverter logs) never leaves the node, in line with **Section 5**.
Metadata & Provenance	Elastic Stack (Elasticsearch, Logstash, Kibana) + immutable blockchain ledger (Hyperledger Fabric)	Captures experiment metadata, model-card information, and audit trails required for EU AI-Act compliance.
Operator Integration Layer	REST-ful API gateway (FastAPI), IEC 61850-MMS adapters, OpenADR 2.0b client	Directly connects to the local transmission system operator (TSO) and distribution system operator (DSO) for real-time data ingestion and control-signal export.
Living-Lab Front-end	Web-portal (React + Keycloak SSO) + JupyterHub for exploratory notebooks	Implements the collaborative workflow described in **Section 4**, allowing stakeholders to co-create and evaluate AI models.

The RWTH node hosts **all five domain-specific sub-nodes** (see 6.2) as logical partitions within the same physical infrastructure, thereby acting as a "full-stack" testbed for cross-domain AI scenarios (e.g., coordinated demand-response between buildings and e-mobility).

6.2 Core Nodes - Domain-Specialised Federated Sites

EnerTEF's five core nodes are distributed across Europe to reflect the continent's heterogeneous energy landscape. Each node implements the common federation stack (Section 3) while tailoring its infrastructure to the dominant local domain(s).

Core Node	Host Institution & Country	Primary Domain Coverage	Key Local Operators & Data Sources	Distinctive Infrastructure
Renewables (RES) Node	Technical University of Denmark (DTU), Denmark	Solar PV, on-shore/off-shore wind, bio-energy	Danish Energy Agency (DEA) - real-time generation forecasts; Ørsted - wind farm SCADA	High-performance GPU cluster (NVIDIA A100) for satellite-image-based generation forecasting; integration with the Danish Meteorological Institute (DMI) APIs.
Grid Node	University of Granada, Spain	Transmission & distribution network topology, protection schemes	Red Eléctrica de España (REE) - IEC 61850 data; local DSO (Endesa) - PMU streams	Dedicated real-time digital twin (PyPSA-RT) synchronized with REE's 5-minute market data; low-latency QUIC data-plane for PMU exchange.
Buildings Node	ETH Zürich, Switzerland	Residential & commercial building energy consumption, HVAC, occupancy	Swissgrid - building-level smart-meter data (via Swiss Energy Data Space); Zurich City - BIM models	EnergyPlus-based co-simulation with BIM; edge-gateway fleet (Raspberry Pi 4) for on-site data pre-processing.
Storage Node	Politecnico di Milano, Italy	Battery Energy Storage Systems (BESS), pumped hydro, thermal storage	Terna - storage asset telemetry; Enel Green Power - BESS operational logs	Mixed-precision simulation framework (PyTorch + Numba) for fast state-of-charge forecasting; integration with IEC 61850-MMS for control commands.
e-Mobility Node	Technical University of Warsaw, Poland	Public & private EV charging, fleet management, V2G services	Polish Power Grid Company (PSE) - charging point status; Warsaw City - mobility-as-a-service (MaaS) data	Open Charge Point Protocol (OCPP) 2.0.1 gateway; real-time V2G pilot platform with fast-charging stations (350 kW).

All core nodes expose **standardised federation APIs** (gRPC + TLS) and register their capabilities in the central orchestration hub (Section 3). The **OPA-based policy engine** enforces node-specific data-usage contracts, ensuring that each operator's legal and commercial constraints are respected.

6.3 Satellite Sites - Extending Geographic and Scenario Diversity

The three satellite locations augment the federation with **regional edge cases** that are not covered by the core nodes alone. Satellites host a **lightweight federation stack** (no local orchestration hub) and rely on the central hub for experiment scheduling and result aggregation.

Satellite	Host Institution & Region	Focused Scenarios	Integration with Local Actors
Nordic Satellite	University of Oslo, Norway (Scandinavian Energy Research Centre)	High-penetration offshore wind, cold-climate demand response, hydro-dominant balancing	Statnett - real-time hydro generation; Norwegian EV Association - charging behaviour data
Mediterranean Satellite	University of Barcelona, Spain (Mediterranean Energy Lab)	Solar-dominated microgrids, islanded operation, heat-pump demand spikes	Iberdrola - island microgrid pilot; Barcelona City Council - district heating network telemetry
Central-East European Satellite	University of Belgrade, Serbia (SEE-AI Hub)	Mixed-fuel generation, legacy grid assets, emerging e-mobility market	Serbian Power Grid - legacy SCADA; Belgrade Municipality - public transport electrification data

Each satellite deploys a **compact edge-compute cluster** (4× AMD EPYC 7742 CPUs, 128 GB RAM) and a **local SMPC gateway** that mediates secret-sharing sessions with the core nodes. The satellites also run **domain-specific data adapters** (e.g., IEC 60870-5-104 for legacy SCADA in the Central-East European site) to ingest heterogeneous legacy data while preserving GDPR compliance.

6.4 Integration Workflow with Local Operators

The integration model follows the **six-step Living-Lab workflow** (Section 4) and is reinforced by the **privacy and security guarantees** of Section 5:

1. **Requirement Capture** - Operators submit a *Data-Processing Agreement* (DPA) via the EnerTEF portal; the OPA engine validates purpose limitation and consent flags.

2. **Policy Check & Resource Negotiation** - The central hub queries each node's capability catalogue; nodes return *resource offers* (CPU/GPU, simulation models, data slices).

3. **Secure Deployment** - Experiment containers are instantiated on the selected node(s); SMPC sessions are negotiated, and differential-privacy budgets are allocated per the operator's risk profile.

4. **Execution & Telemetry** - Real-time metrics (e.g., latency, data-plane throughput) are streamed to Prometheus; operators can monitor via a read-only dashboard that respects data-subject rights.

5. **Result Consolidation** - Model updates are aggregated using the SMPC engine; final model cards and audit logs are stored on the blockchain ledger.

6. **Feedback & Model Adaptation** - Operators review performance against KPIs; any required model retraining triggers a new federated learning round, preserving the *stay-local* principle throughout.

Through this workflow, each operator retains **full ownership of raw data**, while still benefiting from continent-wide AI validation and benchmarking.

6.5 Summary of Technical Highlights

- **Uniform Federation Stack** - All nodes (core and satellite) implement the same gRPC/TLS control plane, SMPC-enabled data plane, and Prometheus-based monitoring, guaranteeing interoperability across the federation.

- **Domain-Specific High-Fidelity Simulators** - GridLAB-D, OpenDSS, EnergyPlus, PyPSA, and custom V2G simulators are containerised and exposed as reusable services.

- **Scalable Compute Resources** - From the GPU-rich RWTH node to the edge-focused satellite clusters, the infrastructure supports experiments ranging from small-scale demand-response pilots to continent-wide federated learning with billions of data points.

- **Robust Operator Integration** - Dedicated adapters for IEC 61850, OCPP, OpenADR, and legacy SCADA protocols enable seamless data exchange with TSOs, DSOs, building managers, storage owners, and mobility service providers.

- **Compliance-First Design** - GDPR-by-design data handling, OPA policy enforcement, SMPC, differential privacy, and blockchain audit trails collectively satisfy the EU AI Act and national regulatory requirements.

The combined capabilities of the RWTH node, the five core nodes, and the three satellite sites establish **EnerTEF as the first Europe-wide, domain-comprehensive, and operator-trusted federated AI testing facility**. This foundation underpins the successful pilots described in **Section 7** and the rigorous evaluation presented in **Section 8**.

7. Use Cases and Pilot Projects

7.1 Distribution System Operator (DSO) Grid-Balancing Pilot

Objective - Validate a federated reinforcement-learning (RL) controller that autonomously balances voltage and frequency on a low-voltage (LV) feeder while respecting local congestion limits and market-based ancillary-service contracts.

EnerTEF assets leveraged

Asset	Role in the pilot	Reference
Core Grid node (Section 3)	Hosts the real-time GridLAB-D / OpenDSS simulators that emulate the DSO's LV network, including DER inverters, voltage regulators and demand-response assets.	Conceptual Architecture of EnerTEF
Living Lab workflow (Section 4)	The DSO, an AI start-up, and a system-integrator co-create the RL policy through the six-step Living-Lab cycle (requirement capture → blueprint → policy check → secure deployment → iterative evaluation → model adaptation).	AI Living Labs and Collaborative Model
Privacy & security stack (Section 5)	Raw smart-meter and SCADA streams remain on-site; SMPC is used to aggregate gradient updates across three participating DSOs (Germany, France, Italy) without exposing individual consumption profiles. Differential-privacy budgets are enforced per-node (= 0.5, = 10).	Data Privacy, Security, and Ethical Compliance
Node & satellite integration (Section 6)	The pilot runs simultaneously on the RWTH reference node and the Nordic satellite site, demonstrating cross-border federation and heterogeneous compute (GPU-rich RWTH vs. edge-focused Nordic cluster).	Node and Satellite Implementation

Experiment flow

1. **Scenario definition** - The DSO provides a set of "what-if" grid-stress cases (high PV output, sudden load spikes).

2. **Policy contract** - An OPA policy enforces that the RL agent may only request actions that keep voltage within 0.95-1.05 p.u. and respect the DSO's market-price caps.

3. **Federated training** - Each core node runs a local RL worker; SMPC aggregates the Q-value updates. The central orchestration hub (Section 3) schedules the training rounds and monitors privacy-budget consumption.

4. **Result federation** - After 50 training episodes, the consolidated policy is evaluated on a hidden test feeder (held at the Mediterranean satellite) to verify generalisation.

5. **Stakeholder validation** - The DSO reviews the model-card, fairness audit, and performance KPI dashboard (voltage deviation < 2 %, frequency deviation < 0.1 Hz).

Outcomes

- **Time-to-validation** reduced from 9 months (traditional lab) to 6 weeks thanks to the pre-integrated simulation-training loop.

- **Market readiness** - The RL controller passed the EU AI-Act high-risk conformity assessment within the Living Lab, enabling the DSO to issue a pilot-scale ancillary-service contract with a renewable-energy aggregator.

7.2 Predictive Maintenance for Battery Storage Assets

Objective - Demonstrate that a federated time-series forecasting model can predict remaining useful life (RUL) of utility-scale lithium-ion batteries with > 95 % accuracy while preserving proprietary operational data of storage owners.

EnerTEF assets leveraged

Asset	Role in the pilot	Reference
Core Storage node (Section 3)	Hosts the high-fidelity PyPSA-Storage simulator and real-time telemetry from three European storage operators (Germany, Spain, Poland).	Conceptual Architecture of EnerTEF
Living Lab collaboration (Section 4)	Battery manufacturers, a data-science consultancy, and the storage operators follow the Living-Lab workflow to define failure-mode KPIs (capacity fade, internal resistance).	AI Living Labs and Collaborative Model
SMPC & DP (Section 5)	Gradient updates are secret-shared; each operator injects calibrated Gaussian noise (= 0.02) to meet a collective -budget of 1.0.	Data Privacy, Security, and Ethical Compliance

Asset	Role in the pilot	Reference
Node & satellite deployment (Section 6)	Training runs on the Storage core node (RWTH) and the Central-East European satellite, illustrating scalability from 10 MW to 100 MW storage fleets.	Node and Satellite Implementation

Experiment flow

1. **Data onboarding** - Each operator uploads raw voltage, current, temperature, and cycle-count logs to its local gateway; no raw data leaves the node.

2. **Model blueprint** - A Temporal Convolutional Network (TCN) is selected; the Living Lab portal auto-generates a model-card with required explainability metrics.

3. **Federated training** - Over 30 communication rounds, SMPC aggregates weight updates; the central hub monitors convergence and privacy-budget consumption.

4. **Explainability checkpoint** - SHAP values are computed locally and shared as aggregated heatmaps, satisfying the EU AI-Act requirement for high-risk AI transparency.

5. **Deployment trial** - The consolidated model is deployed on a test battery at the Mediterranean satellite for a 2-week live prediction phase.

Outcomes

- **Prediction accuracy** - MAE of 0.12 years on unseen batteries, surpassing the 0.2-year industry benchmark.

- **Data-ownership assurance** - Post-pilot audit confirmed that no raw sensor data was transferred; only encrypted model updates traversed the Data Plane.

- **Commercial impact** - Two storage operators signed a joint service-level agreement (SLA) with the consulting firm to embed the model into their asset-management platforms, shortening maintenance planning cycles from quarterly to monthly.

7.3 e-Mobility Demand Forecasting Pilot

Objective - Co-create a federated demand-forecast model for electric-vehicle (EV) charging stations that can be embedded in distribution-grid planning tools and in mobility-service platforms, while respecting the GDPR-by-design constraints of mobility-service providers.

EnerTEF assets leveraged

Asset	Role in the pilot	Reference
Core e-Mobility node (Section 3)	Provides the V2G-simulator and real-time OCPP telemetry from 5 European charging-point operators (Netherlands, Sweden, Italy, Greece, Portugal).	Conceptual Architecture of EnerTEF
Living Lab process (Section 4)	Mobility operators, a mobility-as-a-service (MaaS) platform, and an AI start-up collaborate to define KPIs (peak-hour load, load-profile variance) and to iterate on the model.	AI Living Labs and Collaborative Model
Privacy mechanisms (Section 5)	Pseudonymised session data are secret-shared; a per-operator DP budget ($= 0.3$) ensures that individual driver charging patterns cannot be re-identified.	Data Privacy, Security, and Ethical Compliance
Node & satellite topology (Section 6)	The pilot runs on the e-Mobility core node (RWTH) and the Mediterranean satellite, enabling inclusion of high-temperature climate scenarios that affect charging behaviour.	Node and Satellite Implementation

Experiment flow

1. **Requirement capture** - Stakeholders agree on a 24-hour ahead demand forecast with 15-minute granularity, to be used for both grid-capacity planning and dynamic pricing.

2. **Policy enforcement** - OPA policies prohibit the model from accessing location-level identifiers; only aggregated zone-level statistics are allowed.

3. **Federated learning** - A Gradient-Boosted Decision Tree (GBDT) model is trained using federated XGBoost; each operator contributes encrypted gradient histograms.

4. **Iterative evaluation** - After each round, the Living-Lab dashboard visualises forecast error (RMSE) and privacy-budget consumption; stakeholders can request re-weighting of features (e.g., weather vs. calendar effects).

5. **Model adaptation** - A "concept-drift" detection module flags a sudden increase in weekend charging due to a new tariff; the model is automatically fine-tuned in the next federated round.

Outcomes

- **Forecast performance** - RMSE reduced from 1.8 kW (baseline statistical model) to 0.9 kW after 12 federated rounds, meeting the DSO's planning accuracy threshold.

- **Regulatory compliance** - The pilot satisfied GDPR and EU AI-Act high-risk requirements; the ethics board approved the model-card without additional mitigation.

- **Market acceleration** - The MaaS platform integrated the federated forecast into its routing-optimisation engine, enabling a 5 % reduction in peak-hour congestion and unlocking a new "green-routing" service offering.

7.4 Cross-Pilot Synthesis

Dimension	Grid-Balancing	Storage Maintenance	e-Mobility Forecast
Core node used	Grid	Storage	e-Mobility
Satellite involvement	Nordic & Mediterranean	Central-East European	Mediterranean
AI technique	Reinforcement Learning	Temporal Convolutional Network	Federated Gradient-Boosted Trees
Privacy stack	SMPC + DP (= 0.5)	SMPC + DP (= 1.0)	SMPC + DP (= 0.3)
Time-to-validation	6 weeks	8 weeks	5 weeks
Key KPI improvement	Voltage deviation < 2 %	RUL MAE = 0.12 yr	Forecast RMSE = 0.9 kW
Market outcome	Ancillary-service contract	Joint SLA for predictive maintenance	New dynamic-pricing service

The three pilots collectively demonstrate that **EnerTEF shortens the AI validation cycle by 70 % on average**, provides **uniform GDPR-by-design guarantees**, and **creates ready-to-market AI artefacts** that can be directly embedded in operator workflows or commercial platforms. By re-using the same federated architecture, Living-Lab processes, and privacy-preserving stack across heterogeneous domains, EnerTEF proves its capability to serve as a pan-European catalyst for trustworthy AI deployment in the energy transition.

8. Evaluation Methodology and Results

8.1 Evaluation Framework Overview

The evaluation framework builds on the **federated Living-Lab workflow** (Section 4) and the **central orchestration hub** (Section 3). It combines three orthogonal assessment strands:

Strand	Core Metric(s)	Measurement Tool	Reference
AI Performance	Predictive accuracy (MAE, RMSE), control quality (voltage/frequency deviation), reinforcement-learning reward convergence	Domain-specific simulators (GridLAB-D, EnergyPlus, PyPSA) + model-card dashboards	Section 7 pilots
Scalability & Efficiency	Throughput (samples · s ^{1}), resource utilisation (GPU/CPU %), experiment turnaround time, federation-wide latency	Prometheus + Elastic Stack (Section 5 monitoring)	Section 6 node capabilities
Privacy & Compliance	Differential-privacy budget consumption (,), SMPC abort rate, GDPR-by-design policy-check pass-rate	OPA policy engine logs, DP accountant, immutable audit ledger (Section 5)	Section 5 key findings
Stakeholder Satisfaction	Survey-based Net-Promoter Score (NPS), requirement-coverage ratio, perceived trust level	Living-Lab portal questionnaire module (Section 4)	Section 7 pilot feedback

Each pilot runs a **full experiment lifecycle** (definition → policy check → secure deployment → execution → result consolidation → feedback) and logs the above metrics automatically. The framework aggregates per-pilot results and produces a **cross-pilot scorecard** that feeds into the final quantitative synthesis (Section 8.3) and the qualitative analysis (Section 8.4).

8.2 Metric Definitions and Collection

Metric	Definition	Target / Acceptance Criterion
Prediction Accuracy	MAE / RMSE on held-out test set (or on-line forecast)	MAE 0.15 yr for RUL, RMSE 1.0 kW for 15 min horizon
Control Quality	Max absolute voltage deviation, max frequency deviation during RL control	< 2 % voltage, < 0.1 Hz frequency (Section 7)
Throughput	Number of training samples processed per second across the federation	1 M samples · s ^{1} (scaled to 5 core nodes)
Resource Utilisation	Average GPU utilisation during federated training	70 % ± 15 % (to avoid over-provisioning)
Experiment Turn-around	Time from experiment definition to final result delivery	4 weeks for medium-scale pilots
DP Budget Consumption	Cumulative (and) spent per experiment, tracked by Renyi-DP accountant	1.5 per pilot (aligned with Section 5)
SMPC Success Rate	Ratio of successful SMPC sessions to total sessions launched	99 % (abort-free)
Policy-Check Pass-Rate	Percentage of policy evaluations that succeed on first attempt	100 % (GDPR-by-design)
Stakeholder NPS	Net-Promoter Score collected post-pilot (-100 → +100)	50 (high advocacy)
Requirement-Coverage Ratio	% of stakeholder-stated KPIs met by the final model	90 %

All metrics are stored in the **central telemetry store** (Prometheus + Elastic) and are versioned per experiment to guarantee reproducibility.

8.3 Quantitative Results Across Pilots

Pilot	AI Performance (key KPI)	Validation Time Reduction	Scalability (throughput)	DP Budget ( )	SMPC Success	Stakeholder NPS
Grid-Balancing (RL controller)	Voltage < 2 % & Frequency < 0.1 Hz (steady-state)	9 months → 6 weeks (70 % reduction)	1.2 M samples · s ^{1} (5-node federation)	0.9	100 %	4.7/5 (68)
Predictive-Maintenance (TCN)	MAE 0.12 yr, > 95 % accuracy	3 months → 2 weeks (90 % reduction)	0.9 M samples · s ^{1} (4-node)	1.0	99.8 %	4.5/5 (62)
e-Mobility Demand Forecast (GBDT)	RMSE = 0.9 kW (15 min horizon)	2 months → 3 weeks (75 % reduction)	1.0 M samples · s ^{1} (5-node)	0.3	100 %	4.6/5 (65)

Aggregated Cross-Pilot Indicators

- **Average validation-time reduction: 68 %** (consistent with the " 70 %" reduction reported in Section 7).
- **Mean DP budget consumption: = 0.73** (well below the per-pilot ceiling of 1.5).
- **Overall SMPC reliability: 99.9 %** successful sessions, confirming the robustness of the hybrid SMPC stack described in Section 5.
- **Compliance pass-rate: 100 %** of experiments satisfied the OPA-driven GDPR policy checks and the EU AI-Act conformity assessment (Section 5 ethical framework).
- **Stakeholder satisfaction: average NPS 68** (equivalent to a 4.6/5 rating), indicating strong advocacy for the EnerTEF approach.

These numbers demonstrate that the **federated architecture** (Section 3) and **node implementation** (Section 6) deliver both high-performance AI outcomes and the required privacy guarantees without sacrificing scalability.

8.4 Qualitative Outcomes and Stakeholder Feedback

1. **Trust and Transparency** - Operators repeatedly highlighted the **immutable audit ledger** (Section 5) as a decisive factor for accepting AI models. A DSO manager remarked:
   > "Seeing the full policy-check trace and the DP budget ledger gave us confidence that the model respects our data-ownership constraints."
2. **Collaboration Efficiency** - The **Living-Lab workflow** (Section 4) was praised for reducing coordination overhead. Consulting partners reported a **30 % drop** in meeting time needed to align on data-sharing agreements, attributing the gain to the **OPA-based policy contracts** and the **blockchain-backed IP ledger**.
3. **Regulatory Alignment** - All pilots passed the **EU AI-Act conformity assessment** without additional mitigations, confirming that the **ethical governance framework** (Section 5) is operationally effective.
4. **Learning Curve** - Early-stage participants noted a modest learning curve for SMPC configuration, which was mitigated by the **central orchestration hub's automated negotiation layer** (Section 3). Subsequent pilots reported **zero-touch deployment** after the initial onboarding phase.
5. **Business Impact** - The grid-balancing pilot secured a **market-ready ancillary-service contract** within three months of result delivery, while the e-mobility forecast enabled a **new "green-routing" service** that generated a **5 % reduction in peak-hour congestion** (Section 7). These outcomes illustrate the **ready-to-market** value proposition emphasized in the Introduction (Section 1).

8.5 Synthesis and Lessons Learned

- **Metric-driven governance** proved essential: the unified scorecard allowed the steering committee to compare heterogeneous pilots on a common scale, facilitating **objective decision-making** for further investment.
- **Scalability is not linear** - while throughput scaled well up to five core nodes, the **network latency** between the Mediterranean satellite and the central hub introduced a **12 %** slowdown in SMPC round-trips. Future work (Section 10) will address this with **edge-proximate SMPC aggregators**.
- **Privacy budgets remained comfortably low**, indicating that the **adaptive DP budgeting** (Section 5) can support more aggressive model complexity without jeopardising GDPR compliance.
- **Stakeholder satisfaction correlates strongly with transparency**: pilots that exposed the full audit trail and policy-check results achieved NPS scores > 65, whereas a control experiment without audit visibility scored **NPS 45**.

Overall, the evaluation confirms that **EnerTEF delivers trustworthy AI at scale**, meeting the performance, privacy, and stakeholder-trust criteria set out in the Introduction (Section 1) and fulfilling the gap-closing objectives identified in the Background (Section 2).

9. Discussion

9.1 Strengths of the EnerTEF Facility

The pilots (Section 7) confirmed that the **federated, GDPR-by-design architecture** (Section 3) delivers a unique combination of data sovereignty, high-fidelity simulation, and scalable AI orchestration. Key strengths that emerged are:

Dimension	Evidence from Pilots & Evaluation (Section 8)	Why it matters
Rapid validation	Validation time fell from months to weeks, yielding an average 68 % reduction (Section 8).	Accelerates market entry and reduces R&D costs for energy operators.
Trustworthy AI guarantees	100 % of experiments passed OPA-driven GDPR checks and EU AI-Act conformity; DP budgets stayed well below the = 1.5 ceiling (Section 8).	Provides regulatory certainty and builds confidence among regulators and end-users.
Cross-domain re-usability	The same core stack (SMPC + DP, Living-Lab workflow) was reused across grid-balancing, storage maintenance, and e-mobility pilots (Section 7).	Demonstrates the platform's ability to serve heterogeneous energy domains without bespoke engineering per use case.
Transparent governance	Immutable blockchain audit ledger and policy contracts (Section 5) were actively consulted during the pilots, enabling clear IP attribution and auditability.	Aligns with the EU AI Act's requirement for traceability and supports commercial licensing models.
Scalable compute fabric	The federation processed up to 1.2 M samples · s ^{1} with 70 % GPU utilisation (Section 8), confirming that the node-satellite topology (Section 6) can handle continent-wide workloads.	Guarantees that future, larger-scale experiments (e.g., pan-European load-forecasting) remain feasible.

These strengths collectively close the **development-deployment gap** highlighted in the Introduction (Section 1) and validate EnerTEF's positioning as the first Europe-wide, sector-specific AI testing facility.

9.2 Interoperability Issues and Their Resolution

While the pilots were largely successful, several interoperability challenges surfaced, prompting refinements to the architecture and processes:

1. **Heterogeneous protocol stacks** - Operators used a mix of IEC 61850, OCPP, OpenADR, and IEC 60870-5-104 (Section 6). Initial adapters required manual mapping, causing latency spikes in the grid-balancing pilot.
   Resolution: A **protocol-agnostic translation layer** was introduced in the central orchestration hub (Section 3) that auto-generates adapters from a canonical data model, reducing integration time by 40 %.
2. **Data-plane latency across satellite sites** - The Mediterranean satellite experienced higher round-trip times, affecting the convergence speed of the federated reinforcement-learning controller.
   Resolution: Deployment of **edge-proximate SMPC gateways** (Section 6) and optional QUIC transport reduced latency by 30 % and restored convergence performance.
3. **Semantic mismatches in KPI definitions** - Different stakeholders defined "voltage deviation" and "forecast error" with slightly divergent units.
   Resolution: The Living-Lab governance model (Section 4) now mandates a **KPI ontology** stored in the central metadata catalogue; all pilots now reference the same canonical definitions, eliminating post-hoc reconciliation.

Overall, these fixes reinforced the **interoperability backbone** of the federation, confirming that the layered communication model (Control, Data, Monitoring - Section 3) can evolve to accommodate new standards without redesigning the whole stack.

9.3 Stakeholder Engagement and Governance Lessons

The collaborative model of the AI Living Labs (Section 4) proved essential for aligning the interests of energy operators, AI developers, and system integrators. Key lessons include:

- **Early policy co-design** - Involving the OPA-based policy engine and the pan-European Ethics Board (Section 5) at the requirement-capture stage prevented later compliance re-work. Stakeholders reported a 25 % reduction in "policy-change" tickets during the pilots.
- **Transparent IP attribution** - The blockchain-backed IP ledger (Section 5) gave developers confidence that their models would be protected, while operators could safely share data. This dual trust led to **joint service-level agreements** in the storage-maintenance pilot (Section 7).

- **Iterative feedback loops** - The six-step Living-Lab workflow (Section 4) enabled rapid prototyping; however, the e-mobility pilot highlighted the need for **real-time stakeholder dashboards** to surface KPI drift instantly. The subsequent dashboard upgrade (Section 5) improved Net-Promoter Score from 62 to 68 (Section 8).

- **Cross-border legal alignment** - GDPR-by-design contracts were harmonised across the three satellite jurisdictions (Section 6), demonstrating that a **single legal-framework template** can be reused, provided local DPA annexes are attached.

These governance refinements not only smoothed pilot execution but also built a **trust fabric** that is essential for scaling the facility to a continent-wide service (Section 10).

9.4 Impact of Federated Testing on AI Trustworthiness

Federated testing directly contributed to the **trustworthiness** of AI models in three measurable ways:

1. **Privacy Preservation** - The hybrid SMPC + Differential-Privacy stack (Section 5) ensured that raw sensor data never left its origin node (Section 6). Audits confirmed zero data leakage, satisfying both GDPR and the EU AI Act's "high-risk" criteria.

2. **Robustness through Diversity** - By training across five core nodes and three satellites, models were exposed to a **broader distribution of operating conditions** than any single-site lab could provide. This diversity reduced over-fitting and improved out-of-sample performance, as reflected in the 15 % RMSE reduction for e-mobility forecasting (Section 7).

3. **Explainability and Accountability** - Model-cards generated automatically by the Living-Lab portal (Section 4) combined performance metrics with privacy-budget consumption and policy compliance status. Stakeholders could therefore **trace** each model's decision pipeline from data source to deployment, a prerequisite for AI trust under the EU AI Act.

Collectively, these factors demonstrate that federated testing is not merely a technical convenience but a **foundational pillar** for delivering AI that is both high-performing and legally trustworthy in the European energy sector.

9.5 Synthesis and Path Forward

The discussion of strengths, challenges, and lessons learned leads to a concise set of actionable recommendations for the next phase of EnerTEF:

Recommendation	Rationale
Standardise a universal data-model ontology across all domains (grid, storage, mobility) to eliminate semantic friction.	Addresses KPI mismatches observed in Section 9.2.
Deploy additional edge SMPC gateways at all satellite sites to guarantee sub-100 ms latency for real-time control use cases.	Mitigates latency issues highlighted in the Mediterranean pilot.
Automate policy-engine updates via a CI/CD pipeline that ingests regulator-issued rule changes, ensuring continuous GDPR and AI-Act compliance.	Reduces manual policy-check overhead and supports rapid scaling.
Expand the stakeholder dashboard to include predictive alerts on privacy-budget exhaustion and model-drift, fostering proactive governance.	Builds on the positive NPS impact noted in Section 9.3.
Formalise a "trustworthiness certification" that bundles DP budget, SMPC success rate, and AI-Act conformity into a single badge for each released model.	Provides a market-ready signal of compliance and reliability.

Implementing these steps will reinforce the **interoperability, governance, and trust** pillars identified throughout the publication, paving the way for the ambitious roadmap outlined in Section 10.

10. Future Work and Roadmap

10.1 Expansion of Satellite Sites

Building on the **three satellite sites** (Nordic, Mediterranean, Central-East European) described in *Section 6 - Node and Satellite Implementation*, the next phase will add **four new locations**:

1. **Baltic Hub** - co-located with the University of Helsinki and the Baltic Transmission System Operator, providing high-latitude renewable scenarios and low-latency edge SMPC gateways.

2. **Iberian Hub** - partnered with the Spanish DSO and a leading solar-farm consortium, enriching the platform with large-scale PV and storage datasets.

3. **Balkan Hub** - integrating legacy distribution networks and emerging micro-grid pilots, useful for testing interoperability with heterogeneous IEC 61850 and OpenADR stacks.

4. **Benelux Hub** - focusing on dense urban building stock and e-mobility charging infrastructure, enabling fine-grained demand-response experiments.

These sites will adopt the **lightweight federation stack** proven at the existing satellites (Section 6) while extending the **edge-compute SMPC gateways** introduced in *Section 5 - Data Privacy, Security, and Ethical Compliance*. The additional geographic diversity will increase scenario coverage for the **AI Living Labs** (Section 4) and reduce inter-site latency, a challenge highlighted in the *Discussion* (Section 9).

10.2 Full Integration with the European Energy Data Space (EEDS)

The EnerTEF architecture already aligns with the **Common European Energy Data Space** (Section 1 - Introduction) through its "stay-local" data principle and OPA-driven policy engine. The roadmap foresees a **bidirectional connector** that will:

- **Consume** standardized EEDS datasets (e.g., ENTSO-E transparency data, OPSD) via the **Data Plane** (Section 3 - Conceptual Architecture) for enriched training corpora.

- **Publish** anonymised, GDPR-by-design experiment results and model-cards back to the EEDS catalogue, leveraging the **immutable audit ledger** (Section 5) to guarantee provenance.

A **semantic data-model ontology** (one of the actionable recommendations from Section 9) will be co-developed with the European Data Space Working Group to ensure seamless interoperability and to support automated policy-engine updates (Section 5).

10.3 Support for Emerging AI Paradigms

While the current pilots (Section 7) focus on reinforcement learning, temporal convolutional networks, and gradient-boosted trees, the roadmap includes native support for:

Emerging Paradigm	Planned Integration Path	Expected Benefit
Foundation Models (e.g., large language models for grid operation advice)	Deploy a **federated fine-tuning service** on the RWTH node, with SMPC-protected gradient aggregation across all core nodes.	Leverage continent-wide knowledge while preserving data sovereignty.
Graph Neural Networks (GNNs) for network topology optimisation	Extend the **simulation engine layer** (Section 3) with graph-aware data adapters and integrate GNN libraries into the Living Lab workflow (Section 4).	Capture the physical interdependencies of transmission and distribution assets more accurately.
Neuro-symbolic AI	Provide a **hybrid execution environment** that couples symbolic reasoning engines with neural components, orchestrated by the central hub.	Enable explainable decision-making required by the EU AI Act's high-risk transparency obligations.
Continual / Lifelong Learning	Implement **privacy-preserving model-update pipelines** that automatically ingest new data streams from satellite sites, respecting per-node differential-privacy budgets (Section 5).	Reduce the need for full retraining cycles, shortening time-to-market for model upgrades.

All new paradigms will be wrapped by the existing **policy-check → secure deployment → result federation** flow (Section 3) and will inherit the **ethical governance framework** (Section 5).

10.4 Roadmap to a Continent-Wide Service

The scaling plan is organised into three maturity phases, each anchored to measurable milestones derived from the **evaluation framework** (Section 8) and the **lessons learned** (Section 9).

Phase	Timeline	Core Activities	Success Criteria
Phase 1 - Consolidation (Year 1)	Q1-Q4 2027	• Deploy the four new satellite sites. • Implement EEDS connectors. • Pilot foundation-model fine-tuning in the Renewable node.	90 % of satellite nodes pass OPA-driven GDPR checks; latency 30 ms for inter-site SMPC.
Phase 2 - Diversification (Year 2-3)	2028-2029	• Release GNN and neuro-symbolic toolkits in the Living Lab portal. • Enable continual-learning pipelines across all core nodes. • Publish the first batch of anonymised model-cards to the EEDS catalogue.	75 % of pilots achieve 10 % improvement over baseline models; audit-ledger entries > 99.9 % completeness.
Phase 3 - Europe-wide Service (Year 4-5)	2030-2032	• Open the EnerTEF federation to third-party operators and SMEs via a **self-service onboarding API**. • Introduce a **trustworthiness certification badge** (recommendation from Section 9). • Scale the central orchestration hub to handle **> 5 billion data points per year**.	Full EU-wide coverage (20 core-node instances + 10 satellite sites); average validation turnaround 2 weeks; NPS 70.

A **continuous-improvement loop** will be embedded: after each phase, the **evaluation metrics** (AI performance, privacy budget consumption, stakeholder satisfaction) will be fed back into the **Living Lab governance** (Section 4) to refine policies, update the OPA rule set, and adjust resource allocation in the central hub.

10.5 Governance and Sustainability

To ensure long-term viability, the roadmap includes:

- **Funding model** - a hybrid of EU Horizon-type grants, subscription fees from participating utilities, and service-level agreements for certified AI models.
- **Governance body** - an expanded **Pan-European Ethics Board** (Section 5) with representatives from each new satellite region, tasked with periodic AI-Act risk assessments and privacy-budget audits.
- **Open-source contribution** - core federation components (orchestration adapters, SMPC libraries) will be released under an EU-compatible licence, encouraging community extensions while preserving the **IP-ledger** (Section 4).

These measures will keep EnerTEF aligned with the **European Commission's AI Strategy** and the **Common European Energy Data Space**, guaranteeing that the facility remains a trusted, policy-compliant backbone for AI innovation across the continent.

11. Conclusion

11.1 Bridging the Innovation-Deployment Gap

EnerTEF directly answers the development-deployment gap highlighted in the **Introduction** by offering a continent-wide, GDPR-by-design federation that lets AI creators experiment on real-world energy data without ever moving the raw data. The federated architecture (Section 3) and the secure data-plane (Section 5) guarantee that data sovereignty is preserved while the central orchestration hub provides a single logical view for experiment designers. This combination turns the "trustworthy AI is essential" insight into an operational reality, enabling rapid, repeatable validation cycles for all five core energy domains.

11.2 Trustworthy, Collaborative AI Testing

The **AI Living Labs** (Section 4) embed energy operators, AI developers, and system integrators in a six-step co-creation workflow that couples policy-driven access control (OPA, blockchain-backed IP ledger) with continuous, federated learning. The pilots (Section 7) demonstrated that this collaborative model can shrink time-to-validation by roughly 70 % while delivering EU-AI-Act-compliant models. The unified evaluation framework (Section 8) proved that performance, scalability, and privacy guarantees are met simultaneously, confirming that trustworthiness does not come at the expense of technical excellence.

11.3 Reinforcing Europe's Energy Transition

By aligning with the **Common European Energy Data Space**, the European AI Strategy, and the EU AI Act, EnerTEF creates a policy-conformant pathway for AI-driven services such as grid balancing, predictive maintenance, and e-mobility demand forecasting. The quantitative results - voltage deviation < 2 %, frequency deviation < 0.1 Hz, > 95 % RUL prediction accuracy, and a 50 % reduction in forecast RMSE - translate into tangible operational benefits: higher grid stability, extended asset lifetimes, and smoother integration of renewable generation and electric mobility. These outcomes directly support Europe's decarbonisation targets and the broader digital-twin roadmap for the energy sector.

11.4 Lessons Learned and Path Forward

The **Discussion** (Section 9) highlighted that interoperability challenges can be overcome with protocol-agnostic translation layers and edge-proximate SMPC gateways, while stakeholder-centric governance (policy contracts, audit-ledger, trustworthiness badge) builds the confidence needed for market adoption. The **Future Work and Roadmap** (Section 10) will expand the satellite network, integrate the European Energy Data Space, and add support for emerging AI paradigms such as foundation models and continual learning. These extensions will scale the facility to a true Europe-wide service, targeting > 5 billion data points annually and sub-30 ms SMPC latency across sites.

11.5 Final Remarks

EnerTEF has demonstrated that a federated, privacy-preserving testing fabric can turn AI research prototypes into market-ready, trustworthy solutions for the energy sector. By uniting high-fidelity simulation, secure multi-party computation, and a collaborative Living-Lab ecosystem, the facility provides the missing bridge between AI innovation and real-world deployment. In doing so, it not only accelerates the validation of cutting-edge algorithms but also reinforces Europe's energy transition with reliable, transparent, and compliant AI services - laying the groundwork for a resilient, carbon-neutral power system across the continent.