BOOTCAMP INSIGHTS

Key takeaways from the workshop:

From knowledge to action

AI workshop outcomes & expert insights

USE CASE 2

REDUCTION OF NON-TECH LOSSES

This summary reviews what was produced by the participants during the workshop, complemented by the analyses and recommendations of our AI experts.

THE WORKING GROUP'S PERSPECTIVE

Target users

- **Distribution companies** managing electricity networks and billing
- **Social actors** involved in local energy access and community programs
- **Impact investors** seeking measurable economic and social outcomes

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Who Benefits from This Use Case

This use case is primarily designed for **utilities and grid operators** operating in regions with **high levels of non-technical losses (NTL)**. In these contexts, revenue leakage caused by fraud, theft, or unbilled consumption represents a major operational and financial challenge. By leveraging AI, these actors can better identify where losses occur and focus their efforts where the impact is highest.

Aligning Stakeholders for Sustainable Impact

Reducing non-technical losses cannot be addressed by utilities alone. It requires early and continuous **alignment with key stakeholders**, including regulators, local authorities, and impact investors. Engaging these actors from the outset helps ensure regulatory compliance, reinforces transparency, and builds community support. This alignment is essential to balance enforcement, social considerations, and long-term trust.

Focusing Deployment Where Losses Are Highest

Rather than deploying solutions uniformly across the network, the approach prioritizes **high-loss zones**. By using loss heatmaps and **feeder-level rankings**, utilities can clearly identify the areas where non-technical losses are most concentrated. This targeted deployment maximizes impact while optimizing the use of operational and financial resources.

Adaptive and Context-Aware Detection

The solution relies on **agentic AI** capable of adapting its detection strategies to local realities. Instead of applying a single, static model, the AI adjusts its analysis based on **local consumption patterns**, **customer profiles**, and **historical fraud signatures**. This adaptive behavior improves detection accuracy and reduces false positives.

Advanced Targeting Through Data and Geospatial Analysis

To further refine interventions, the approach combines **geospatial clustering** with **anomaly detection** techniques. This allows utilities to concentrate investigations on areas where loss density is the highest, such as specific neighborhoods or feeders. As a result, field actions become more focused, efficient, and defensible from both an operational and regulatory standpoint.

THE WORKING GROUP’S PERSPECTIVE

Objective

- **Reduce electricity theft** by identifying abnormal consumption patterns
- **Increase revenue** through improved billing accuracy and loss recovery
- **Increase the number of legitimate connections** to the network
- Enable **more efficient network sizing** based on reliable consumption data

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Defining Clear and Measurable Objectives

When deploying an AI-driven solution, it is essential to define **focused and measurable objectives**. Clear goals help avoid dispersion, align teams, and make it easier to assess the real impact of the solution over time. Using a SMART approach ensures that objectives are concrete, time-bound, and actionable.

Examples of SMART Objectives

One possible objective is to **reduce non-technical losses by 15% in high-loss zones within the next 12 months**. This can be achieved by combining AI-driven anomaly detection with targeted field interventions in the areas most affected.

Another objective is to **improve billing accuracy by 10% across all monitored feeders within 6 months**. This relies on integrating AI-based validation mechanisms while keeping **human-in-the-loop checks** to secure reliability and trust in the results.

Finally, a clear financial objective can be set by aiming to **recover at least X k€ in lost revenue within the first year**. This is achieved by prioritizing fraud detection and streamlining resolution workflows, ensuring that identified issues translate into concrete financial gains.

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Benefits

- **Reduced electricity theft** through early detection of abnormal usage
- **Increased revenue** by recovering unbilled or lost energy
- **More legitimate connections** to the grid and improved access management
- **More efficient network sizing** based on accurate consumption insights
- **More effective community programs** enabled by better targeting and data-driven interventions

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Strengthening Revenue Protection

The primary impact of this approach is **stronger revenue protection**. By reducing non-technical losses and improving billing accuracy, utilities are able to recover a greater share of previously lost revenue. These gains translate directly into improved financial performance and a more sustainable business model.

Building Operational Confidence and Trust

The use of AI enables **faster and more consistent investigations**, while reducing the number of false positives. As a result, operational teams gain confidence in the signals they receive, and regulators develop greater trust in the detection and decision processes. This consistency supports more defensible and transparent actions.

Creating Long-Term Value Through Data Leverage

Beyond immediate loss reduction, the solution strengthens the overall **data foundation** of the organization. Higher-quality, better-structured data can then be reused to support adjacent grid analytics use cases, such as forecasting, maintenance, and network planning, creating long-term value beyond the initial use case.

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Pain points

- Uncertainty on **how to address theft and unavoidable losses** in a fair and effective way
- Difficulty ensuring **reliable, consistent, and trustworthy data collection** across the network

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Data Quality and Availability Challenges

A major limitation lies in **data quality gaps**. Meter data can be incomplete or inconsistent, historical records may be missing, and information is often spread across fragmented sources. These issues reduce the reliability of AI models and limit their ability to detect non-technical losses accurately.

Limited Real-Time Visibility

Effective detection of anomalies requires **granular and up-to-date data**. However, limited access to real-time AMI or IoT data makes it harder to identify suspicious usage patterns quickly, delaying response and reducing overall effectiveness.

Constraints on Field Investigation Capacity

Even when anomalies are detected, **field teams may lack sufficient resources or appropriate tools** to investigate flagged cases rapidly and thoroughly. This gap between detection and action can weaken the operational impact of the solution.

Community Acceptance and Social Resistance

In some contexts, **local mistrust or resistance** toward anti-fraud initiatives can significantly reduce their effectiveness. Without proper engagement and communication, enforcement actions may face pushback and limit long-term results.

Fragmented Systems and Limited Coordination

Disconnected **billing, metering, and analytics systems** make it difficult to coordinate responses across teams. This fragmentation prevents end-to-end visibility and slows down decision-making and execution.

Trust and Explainability Issues

The use of **black-box AI models** can create explainability challenges. When results cannot be clearly explained, trust decreases among field teams and regulators, making adoption and operational use more difficult.

Governance and Oversight Gaps

Finally, unclear **data access rights**, poorly defined **model update processes**, and a lack of structured oversight mechanisms create governance gaps. These weaknesses increase operational risk and hinder sustainable deployment of AI-driven solutions.

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Prerequisites

- **Relevant and reliable data** to analyze consumption and billing patterns
- **Adequate hardware** to collect, store, and process data
- **Operational resources** to investigate and act on AI-identified cases
- **Data protection measures** to ensure privacy, security, and regulatory compliance

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Adapting Prerequisites to the Level of Ambition

The level of prerequisites depends on the **ambition of the use case** and the **value expected from the solution**. A pragmatic approach is to align technical, organizational, and governance requirements with the maturity level targeted.

Basic Value: Starting with Limited Requirements

At an initial stage, organizations can focus on **quick validation and learning**. This typically involves launching a **pilot in a single high-loss area** to test the approach and measure initial KPIs. Existing data sources and **simple workflows** are sufficient to support early anomaly detection and basic field validation. This phase helps demonstrate value while limiting complexity and investment.

Higher Value: Enabling Advanced Capabilities

To unlock greater impact, more advanced prerequisites are required. **Data readiness** becomes critical: data must be complete, up to date, and secured through regular audits, automated quality checks, and robust data pipelines. Extending AMI or IoT coverage improves granularity and real-time visibility.

At the same time, **capabilities and governance** must be reinforced. Teams need training on AI tools, as well as on privacy and ethical considerations. Clear decision rights, human oversight mechanisms, and structured governance for data access and model updates are essential to ensure regulatory compliance and trust.

Scaling Through Continuous Improvement

Finally, achieving maximum impact requires **iterative scaling**. By instrumenting KPIs, refining detection models and workflows, and progressively expanding deployment to multiple regions, organizations can continuously improve performance while scaling the solution in a controlled and measurable way.

THE WORKING GROUP'S PERSPECTIVE

Detailed description

- **AI predictive models** compare expected consumption with observed usage
- **AI detects usage anomalies** that may indicate theft or irregular connections
- **AI analyzes the gap between kWh distributed and kWh billed** to identify non-technical losses
- **ML models and LLMs are combined** to both detect patterns and explain results

How it works in practice:

The AI system continuously compares historical and expected consumption patterns with real usage data. When significant deviations appear, the models flag potential anomalies. Machine learning models focus on detecting and quantifying abnormal behaviors, while large language models help interpret these results, explain them to operational teams, and support decision-making on appropriate follow-up actions.

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Establishing a Reliable Baseline for Detection

The detection process starts with a **baseline comparison**. AI agents continuously compare consumption time-series with expected usage profiles. When significant deviations appear, these irregularities can indicate potential tampering, fraud, or abnormal behavior that requires further investigation.

Combining Complementary Detection Approaches

To improve robustness, the solution relies on a **dual detection strategy**. Unsupervised anomaly detection is used to uncover new or unexpected patterns that were not previously identified, while supervised models are trained on labeled fraud cases to recognize known fraud behaviors. Together, these approaches increase detection coverage and accuracy.

Keeping Humans in the Decision Loop

Despite automation, **human validation remains essential**. By keeping a human-in-the-loop, utilities can reduce false positives and ensure that actions taken are defensible, especially in sensitive contexts involving customers, regulators, or legal follow-up.

Enriching Decisions with Context Through RAG

For each flagged incident, **Retrieval-Augmented Generation (RAG)** is used to provide relevant context. This includes regulatory guidance, similar historical cases, and customer-specific information. Access to this context helps teams understand situations more quickly and make informed decisions.

Enabling Efficient Field Execution

Detection alone is not sufficient without effective execution. The integration of **mobile tools** allows field teams to receive assignments directly, capture evidence on-site, and close cases efficiently. This ensures a smooth transition from analysis to action.

Leveraging Spatial Analytics for Targeted Actions

Finally, the approach uses **spatial analytics**, combining graph-based anomaly detection with geospatial clustering. This makes it possible to isolate suspicious neighborhoods or feeders, enabling more targeted and coordinated field interventions.

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