AMI 3.0 concept: Untap the power of AI and dynamic load management

Ihab Mokhles
Cuculus GmbH, Germany
Ihab.Mokhles@cuculus.com

Arndt TELSCHOW
Cuculus GmbH, Germany
arndt.telschow@cuculus.com

Susanne Zeglin
Cuculus GmbH, Germany
susanne.zeglin@cuculus.com

René BÖRINGER
Cuculus GmbH, Germany
rene.boeringer@cuculus.com

Artemy Voroshilov
Cuculus GmbH, Germany
artemy.voroshilov@cuculus.com

Lars MOLSKE
Cuculus GmbH, Germany
lars.molske@cuculus.com

Introduction

Challenges Facing Energy Utilities

Energy utilities worldwide face several pressing challenges that threaten their operations, profitability, and customer satisfaction. Fraud and revenue assurance issues, such as electricity theft and non-technical losses, contribute to significant financial losses—estimated globally at $80-100 billion annually. These losses directly impact utilities' ability to invest in infrastructure, leading to reduced grid reliability and slower modernization efforts. In addition, utilities grapple with grid resilience and service stability. As grids become more interconnected and complex, managing system stability in the face of natural disasters, technical failures, and cyber-attacks becomes increasingly difficult. Compounding these issues is the challenge of solving the supply and demand gap, particularly in developing regions. Rapid urbanization, increasing energy demands, and the integration of renewable energy sources add layers of complexity to balancing energy supply and demand efficiently.

The Evolution of Advanced Metering Infrastructure (AMI)

Over the years, the evolution of Advanced Metering Infrastructure (AMI) has aimed to address some of these challenges. AMI 1.0 introduced the basic elements of smart metering, allowing utilities to remotely collect meter data and eliminate the need for manual meter reading. However, this early version of AMI primarily focused on automating billing processes without tackling more dynamic grid challenges. AMI 2.0 marked a significant improvement, integrating two-way communication between utilities and consumers. This version enabled utilities to offer demand response programs, enhance outage management, and begin exploring data-driven grid management solutions. However, despite these advancements, AMI 2.0 still falls short of meeting the modern challenges of fraud detection, dynamic load management, and optimizing energy usage in real-time.

The Power of AI and Data Analytics

The rise of Artificial Intelligence (AI) and data analytics has opened new opportunities to address these longstanding issues. AI-driven solutions, combined with advanced data analytics, offer utilities the capability to identify fraudulent activities in real-time, improve grid resilience through predictive maintenance, and optimize supply-demand balance by anticipating consumption patterns. These technologies enable more accurate demand forecasting, efficient resource allocation, and proactive responses to grid instability. In the following sections of this paper, we will delve into four key applications of AI and data analytics that demonstrate their transformative potential in solving the challenges of revenue assurance, grid resilience, service stability, and balancing energy supply and demand. This comprehensive integration of AI and data analytics is what we believe should define AMI 3.0.

Harnessing AI and machine learning in Fraud Detection

Energy and water utilities are plagued by non-technical losses, particularly fraud and theft. These losses contribute to a global revenue deficit of $80 to $100 billion annually, with 30-50% of generated energy lost through electricity theft and unbilled consumption. These financial losses hinder utilities' ability to maintain infrastructure, invest in innovations, and ensure efficient service delivery. Traditional approaches to loss detection, which rely heavily on random on-site inspections, are costly and ineffective, often resulting in poor targeting of actual fraudsters.

Flaws in Conventional Methods

Random inspections are inefficient because they lead to high operational costs (e.g., labor and vehicle expenses) without guaranteed results. As utilities expand and smart grids grow, relying on random inspections becomes unsustainable. The process fails to identify fraudulent activity accurately, increasing the burden of "truck rolls" while offering little return on investment. To address this, utilities need a smarter, AI-driven approach to target high-risk customers more precisely, reducing unnecessary inspections and operational costs.

The experiment focuses on a classification problem using machine learning (ML) to detect fraudulent behavior in smart meter data and identify customers engaging in electricity theft. A random forest classifier is implemented Cuculus ZONOS™ FraudDetect, which combines multiple decision trees to distinguish between fraudulent and non-fraudulent customers. This robust ML technique effectively handles large datasets and minimizes overfitting, making it particularly suitable for enhancing fraud detection in utilities. Once trained, the model iteratively improves by incorporating results from on-site inspections, which verify the predictions made by the model. With each round of inspections, the model is retrained using the new labelled data, enhancing its ability to correctly classify customers as fraudulent or honest. The experiment follows a well-structured process:

1. **Initial Data Setup:** A labelled dataset of 42,372 smart meters from the State Grid Corporation of China (SGCC) was used, with 3,615 cases of fraud and 38,757 honest customers. This data was balanced using the SMOTE (Synthetic Minority Over-sampling Technique) algorithm to generate a dataset containing 77,514 time series.

2. **Iterative Process:** Initially, the classifier is untrained, and the first set of inspections is based on random predictions. Over time, the model improves by continuously retraining itself on the results from on-site inspections.

3. **Metrics and Analysis:** The metrics used include accuracy, precision, recall, and F1-score, as well as the hit rate, the percentage of correct fraud detections from on-site inspections.

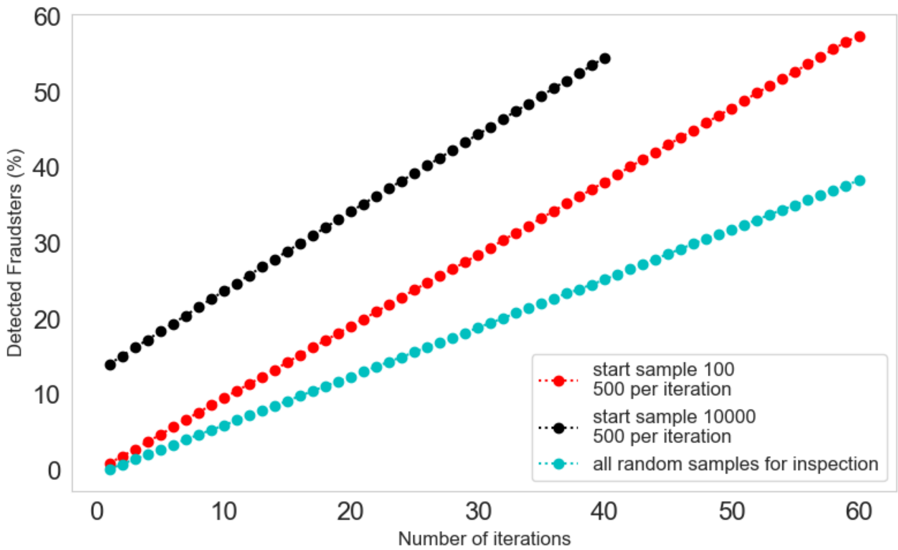

Figure 1: detected Fraudsters % Over Iterations

Key Findings

- **Precision and Iteration**: Precision improves as the number of iterations increases, from 75% initially to nearly 90% after multiple rounds of training. This proves that AI can significantly improve fraud detection over time
- **Decreasing Hit Rate**: Despite increasing precision, the hit rate decreases as fewer fraudsters remain in the dataset after multiple rounds of detection. This suggests that the model becomes increasingly efficient at finding fraud, but as the pool of fraudsters shrinks, it becomes harder to maintain high hit rates.
- **Sampling Strategy**: The study found that using smaller initial sample sizes and adjusting the sample size per iteration maximizes the overall hit rate. An optimal strategy was achieved with a start sample size of 500 and an iteration sample of 1000, yielding the highest hit rates.

Thus it is safe to say that by adopting this AI-driven approach, utilities can realize significant cost savings and improve revenue collection:

- **Reduced Operational Costs**: AI enables more targeted on-site inspections, potentially reducing unnecessary truck rolls by 40-50%. Fewer random inspections translate directly into lower fuel, labor, and vehicle maintenance costs.
- **Improved Revenue Collection**: More accurate fraud detection leads to fewer non-technical losses. Assuming an average 30-50% reduction in energy theft, utilities could see a revenue boost of annually, that would be used for more capital expenditure in the network.

Revolutionizing Demand Forecasting with AI and Neural Networks

Effective demand forecasting is critical for utilities to manage supply efficiently and maintain grid stability. Traditional models often fail to capture the complexities and dynamics of energy consumption patterns, resulting in inaccurate forecasts and operational inefficiencies.

Conventional demand forecasting models, such as ARIMA (Auto Regressive Integrated Moving Average) and linear regression, rely heavily on historical consumption data and tend to assume a linear relationship between inputs and outputs. While useful for basic forecasting, these models often fall short in accuracy, especially in the context of non-linear consumption patterns driven by various factors, including weather changes, economic conditions, and the growing integration of renewable energy sources. As highlighted in the paper, these limitations can lead to significant discrepancies between forecasted and actual demand, which can adversely affect utilities' ability to manage their resources effectively.

AI and Neural Networks in Demand Forecasting

To address the complexity of power grid forecasting, machine learning (ML) and artificial intelligence (AI) approaches, particularly neural networks, are increasingly being used. These models excel at capturing complex dependencies in large datasets, often outperforming traditional linear forecasting methods. However, they have notable downsides: they require extensive training data, are difficult to transfer across different systems, and can be opaque and challenging to maintain. Moreover, neural networks primarily encode correlations rather than causations, leading to a decline in forecast accuracy over time and the need for frequent retraining.

Proposed Data Analytics Model

Cuculus introduces an alternative data analysis framework for power and water demand forecasting, combining machine learning, dynamic systems theory, and causal inference. Unlike traditional linear methods or neural networks, this framework delivers more accurate forecasts for nonlinear and high-dimensional systems by focusing solely on historical data and causal drivers, avoiding spurious correlations. A key benefit is its adaptability, as it does not require retraining when conditions change, such as during a pandemic or when applied to different power grids. The paper demonstrates that the Causal Forecasting method outperforms most European transmission system operators (TSOs) in univariate forecasting and discusses the advantages of causal inference for multivariate forecasting.

The model analyses time-series data from four European countries—Germany, Austria, Hungary, and the Netherlands—focusing on actual total load and day-ahead load forecasts from Transmission System Operators (TSOs). The data, covering the period from October 1, 2017, to December 31, 2023, was obtained from the ENTSOE website and includes one data point every 15 minutes. For Germany, the data pertains to the region managed by the largest TSO, Tennet. The analysis used nonlinear time series techniques, specifically state-space reconstruction, optimized for electric load forecasting but adaptable for other critical infrastructures like water systems. Custom programs in R and Python were used to conduct 24-hour-ahead forecasts for every 15-minute interval across all countries for the five-year period from January 1, 2019, to December 31, 2023 (the analysis for the Netherlands was conducted only until December 31, 2021).

Result of Data Analytics

We analysed the forecast accuracy for all four countries and for the entire three-year period (Table I). For Germany, we found that the mean forecast error of the local transmission system operator for the years 2019 to 2023 was between 5.32% and 8.98%, but for *Causal Forecasting* it was between 3.31% and 4.79%. This means that the forecast from *Causal Forecasting* for 2019 to 2023 is consistently better than that of the local TSO.

	2023	2022	2021	2020	2019
Germany					
Local TSO	8.98%	7.44%	7.62%	5.32%	6.68%
Causal Forecasting	4.79%	4.01%	3.49%	3.31%	3.34%
Austria					
Local TSO	3.27%	3.04%	3.59%	5.46%	4.55%
Causal Forecasting	3.9%	3.22%	3.52%	4.0%	3.53%
Hungary					
Local TSO	4.73%	4.50%	4.74%	4.48%	4.21%
Causal Forecasting	4.91%	4.01%	3.77%	3.35%	3.66%
Netherlands					
Local TSO	-	-	8.07%	10.69%	15.45%
Causal Forecasting	-	-	6.10%	3.65%	3.14%

Table 1 : Summary statistics of forecast errors

The results are more remarkable given that the analysed the period from 2019 to 2023 included years of abrupt and drastic changes in electricity consumption due to lockdowns during the coronavirus pandemic. Throughout this time, Causal Forecasting consistently provided good forecasts, even though only historical load data was used for forecasting. This shows that Causal Forecasting adapts quickly to different situations, be it a new country or a new time with new consumption patterns.

The strictly univariate approach offers a number of simple ways to improve the forecast accuracy of Causal Forecasting. The easiest way would be to account for public holidays, especially when public holidays fall on a weekday. A further possibility opens up when data is not only available for the overall system (e.g. electricity consumption in a country), but also for its subsystems (e.g. electricity consumption in cities or distribution stations). A prediction for the overall system can then be made by summing up forecasts that were created individually for the subsystems. For nonlinear complex systems such as power grids, it can be expected that this will lead to a significant improvement in forecast quality.

Adopting this advanced forecasting approach offers numerous benefits for utilities. By improving forecasting accuracy, utilities can achieve better load balance, minimize operational costs related to demand mismanagement, lower reliance on costly peak power plants, which are typically used during periods of high demand, and effectively close the gap between energy supply and consumption.

The Causal Forecasting method has been implemented in commercial software and is publicly available as a live forecast demo at https://24insight.zonos.de/. New total load data from the four countries are downloaded from the ENTSOE website every 15 minutes. With this data, new live forecasts are generated using Causal Forecasting, with computer runtime being less than a second. The actual and forecast data are then displayed graphically along with a table comparing the forecast accuracy of the Causal Forecasting forecast to that of the local TSO.

Unleashing Data Analytics for Enhanced Grid Resilience

One of the most critical challenges in managing power grids is maintaining a balance between supply and demand. Any imbalance can lead to destabilization, resulting in poor power quality, blackouts, or even large-scale outages. Traditional methods of grid monitoring often struggle to predict such failures, especially as modern grids become more interconnected and complex. These complexities increase the risk of tipping points that can cause cascading failures, which are difficult to prevent with conventional methods.

Conventional grid monitoring techniques are not well-equipped to handle the systemic risks that arise from the increasing complexity of modern power grids. These methods typically focus on localized issues without accounting for the intricate, interconnected nature of today’s distribution networks. As a result, they fail to anticipate critical system-wide failures that could occur due to infrastructure degradation, sudden demand surges, or extreme weather events.

Dynamic Systems Theory for Resilience Monitoring

Cuculus introduces an innovative approach based on dynamic systems theory and nonlinear time series analysis to monitor the resilience of power grids. By treating the grid as a complex nonlinear dynamical system, we use the Kuramoto model of coupled oscillators to simulate grid behavior. This model enables more realistic simulations of grid failures by capturing key features of power grids, such as phase synchronization, and by taking into account the growing integration of renewable energy sources, which can impact grid stability.

At the heart of this new method is the Network Resilience Index (NRI), which is calculated from voltage time series data. The NRI is used to assess whether a grid is stable or nearing a tipping point that could lead to failure. The NRI is based on bifurcation theory, which mathematically predicts the likelihood of critical transitions (grid collapses) by analysing the system's dominant eigenvalue. A high NRI value indicates that the grid is approaching a critical state, while low values signify stability.

Model Setup and Process

The model simulates two key scenarios using a star-shaped distribution network to illustrate the effectiveness of the NRI:

1. **Scenario 1: Grid Degradation** – In this scenario, grid failure is simulated due to the gradual degradation of infrastructure, mimicking the impact of aging power lines, rising electricity demand, or increased use of renewable energy sources. The results show that the NRI steadily increases as the system approaches failure, offering a clear early warning sign

2. **Scenario 2: Extreme Events** – Here, the grid is subjected to sudden disturbances, such as lightning strikes or short circuits, to analyze how it reacts to shocks. For resilient systems, the NRI temporarily spikes but quickly returns to normal levels, indicating recovery. In less resilient grids, the NRI remains elevated, predicting a collapse. This scenario demonstrates the model’s ability to assess vulnerability to extreme events.

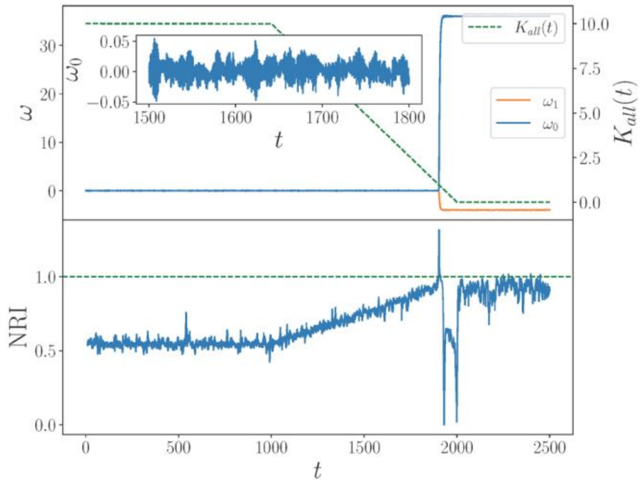

Figure 2: NRI values rising as the grid degrades, indicating an approaching failure.

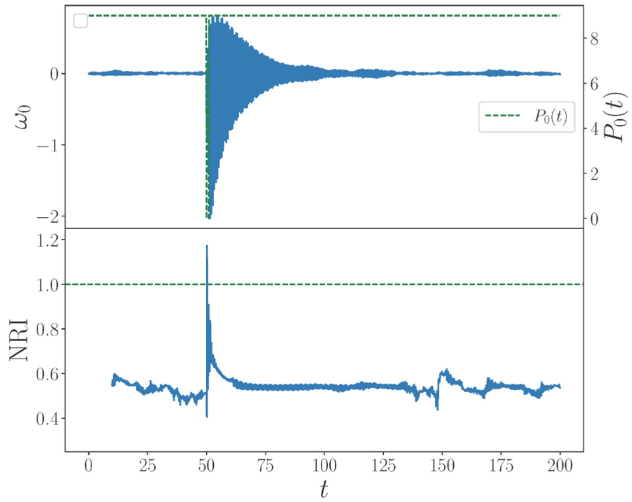

Figure 3: NRI values during an extreme event, with resilient grids recovering quickly and vulnerable grids collapsing.

The results demonstrate the effectiveness of *NRI* for monitoring network resilience. This new monitoring method offers a wide range of possible uses in distribution systems. Thus, Network Resilience Index offers several advantages for utilities:

- **Early Warning of Failures**: By continuously monitoring the NRI, utilities can identify when their grids are approaching critical tipping points. This allows for timely intervention, preventing large-scale blackouts or other system failures.
- **Improved Planning and Maintenance**: The NRI provides actionable data that can be used to prioritize infrastructure upgrades and maintenance efforts. Utilities can allocate resources more efficiently, focusing on areas of the grid that show signs of weakening resilience.
- **Response to Extreme Events**: The model's ability to assess a grid's vulnerability to extreme events helps utilities prepare for and mitigate the impact of sudden disturbances. This enhances grid reliability and reduces the risk of prolonged outages.
- **Optimizing Renewable Integration**: As renewable energy becomes more prevalent, managing its impact on grid stability is increasingly important. The NRI can help utilities assess how the integration of renewables affects grid resilience and take measures to maintain stability.

Edge Computing in Smart Meters for Enhanced Performance

Edge computing refers to the practice of processing data near the source of data generation rather than relying solely on centralized cloud computing. In the context of smart meters, edge computing can significantly enhance data processing efficiency, reduce latency, and improve the overall responsiveness of power grid management systems. Smart meters equipped with edge computing capabilities can perform local data analysis and decision-making and hence provide a range of applications that significantly enhance the operational efficiency and effectiveness of distribution companies. Here are several key applications:

Real-Time Load Monitoring and Management

Edge computing allows smart meters to continuously monitor energy consumption patterns in real time. This capability enables distribution companies to:

- **Balance Load**: Identify and respond to peak load conditions by dynamically adjusting energy distribution, thus preventing overloads and maintaining grid stability.
- **Demand Response**: Implement demand response programs where consumers are incentivized to reduce or shift their energy usage during peak periods. Smart meters can communicate with consumers directly, enabling real-time adjustments.

Advanced Fraud Detection

With edge computing, smart meters can analyze consumption data locally to detect anomalies indicative of fraud or energy theft:

- **Anomaly Detection**: Smart meters can identify patterns that deviate from historical data (e.g., sudden spikes in usage) and flag these for further investigation, reducing losses associated with non-technical losses.
- **Immediate Alerts**: When a potential fraud incident is detected, the system can send alerts to utility operators in real time, enabling prompt action to investigate and mitigate losses.

Integration of Renewable Energy Sources

As the integration of renewable energy sources (like solar panels and wind turbines) into the grid increases, smart meters with edge computing play a crucial role:

- **Distributed Energy Resource Management**: Smart meters can optimize the integration of distributed energy resources (DERs) by analysing generation and consumption data locally, allowing for efficient energy management and grid stability.
- **Load Shifting**: The system can shift loads based on the availability of renewable energy, encouraging consumption during periods of high generation (e.g., during sunny or windy days).

Digital Twin of the LV Distribution Network

Smart meters equipped with edge computing can contribute significantly to the creation and maintenance of a **digital twin** of the distribution network:

- **Real-Time Simulation**: A digital twin is a virtual representation of the physical grid that continuously updates based on real-time data from smart meters. This allows utilities to simulate various scenarios and predict how changes will affect the system.
- **Enhanced Decision-Making**: By analysing real-time data, utilities can optimize operations, test new strategies, and predict the impacts of infrastructure changes without the risks associated with physical alterations.

- **Performance Monitoring**: The digital twin can be used to monitor the performance of the distribution network continuously, enabling proactive maintenance and immediate adjustments based on predictive analytics.

In conclusion, the use of edge computing modules in smart meters represents a significant advancement in the management of power systems. By enabling real-time data processing, it empowers utilities to optimize their operations and respond proactively to changing grid conditions. This integration is crucial for building a resilient, efficient, and sustainable energy infrastructure that meets the demands of the future.

Conclusion

This paper has presented a comprehensive exploration of what we believe is AMI 3.0 concept, focusing on how AI, data analytics, and edge computing can transform the energy sector. From tackling non-technical losses like fraud to enhancing grid resilience and improving demand forecasting, the integration of advanced technologies is key to addressing the challenges faced by modern utilities.

The first section examined how AI-driven loss detection can significantly reduce operational costs and improve revenue collection by optimizing fraud detection processes. Traditional methods, such as random inspections, are no longer sufficient, and AI provides a more accurate and efficient alternative.

Next, we explored how AI and neural networks can revolutionize demand forecasting. By moving beyond traditional linear models and leveraging causal inference and nonlinear time series analysis, utilities can better predict demand and reduce reliance on costly peak power plants. The analysis of data from multiple European countries demonstrated the superior accuracy of Causal Forecasting, especially during unpredictable times, such as the COVID-19 pandemic.

In the third section, we delved into the use of dynamic systems theory to monitor grid resilience. The Network Resilience Index (NRI) offers utilities a powerful tool for identifying potential grid failures before they occur, allowing for proactive maintenance and improved integration of renewable energy sources. This model not only improves the ability to predict failures but also enhances grid stability in response to extreme events and infrastructure degradation.

Finally, we discussed the role of edge computing in smart meters. By enabling local data processing, smart meters with edge computing modules offer real-time load management, advanced fraud detection, better integration of renewable energy, and the creation of a digital twin of the distribution network. These innovations provide distribution companies with the tools to optimize grid operations and improve decision-making.

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