Case Study · Smart Meter Analytics

Artificial Intelligence · Smart Grid · Grid Analytics

AI-Powered Smart Meter Analytics

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Index Terms

Artificial Intelligence · Smart Grid · Load Forecasting · Grid Analytics · Customer Experience · Saudi Arabia · Vision 2030

Abstract — The Middle East's power sector is undergoing rapid modernization, driven by the need for greater operational efficiency, grid resilience, and customer-centric services. This paper presents an integrated framework for AI-powered smart meter analytics that transforms raw consumption data into actionable grid intelligence. The methodology begins with accurate Source-of-Supply (SoS) identification to establish reliable meter-to-transformer mapping [7], followed by Non-Intrusive Load Disaggregation (NILD) for appliance-level insights [2], [3]. These outputs feed anomaly detection models—including clustering, isolation forests, deep learning, and graph neural networks—to identify fraud and non-technical losses in near real time [14]–[18]. Transformer Load Monitoring (TLM) and hybrid forecasting models (LightGBM and SARIMAX) enable predictive capacity management and proactive asset planning [8]. Complementary modules, including the Electrical Loss Dashboard [6], [8] and Guaranteed Standard process [6], [7], improve outage analysis, reduce financial losses, and automate service compensation workflows. Continuous AI feedback loops support adaptive learning, while GenAI-driven decision tools provide actionable insights for planners, operators, and customers across the region.

Deployed at scale, this ecosystem has demonstrated measurable financial impact, including recovery of unbilled energy [14], [15], reduction of technical and non-technical losses [3], [6], and deferral of capital expenditures [9]. Beyond financial gains, the framework enhances grid resilience, supports renewable integration, and empowers consumers with personalized energy insights. By embedding AI across the electricity value chain, Saudi utilities can shift from reactive operations to proactive, data-driven grid management—setting global benchmarks for smart grid innovation and customer service excellence.

Nomenclature

1) Acronyms & Abbreviations

AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
BESS	Battery Energy Storage System
CM	Consumer Meter
CNN	Convolutional Neural Network
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DERMS	Distributed Energy Resource Management System
DT	Distribution Transformer
DSM	Demand Side Management
ECA	Efficient Channel Attention
ERR	Energy Recovery Ratio
EV	Electric Vehicle
GAN	Generative Adversarial Network
GIS	Geographic Information System
GNN	Graph Neural Network
kWh	Kilowatt-hour
LGBM	Light Gradient Boosting Machine
LSTM	Long Short-Term Memory network
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
NEMA	National Electrical Manufacturers Association
NILD	Non-Intrusive Load Disaggregation
NTL	Non-Technical Losses
OPEX	Operating Expenditure
RM	Reference Meter
SARIMAX	Seasonal ARIMA with Exogenous regressors
SM	Smart Meter
SoS	Source of Supply (meter-to-transformer mapping)
SVM	Support Vector Machine
TLM	Transformer Load Monitoring
TWh	Terawatt-hour
VPP	Virtual Power Plant

2) Mathematical Symbols

$L_i(t)$	Load of consumer i at time block t (kW)
N	Number of consumers connected to a transformer
L_T(t)	Total transformer load at time block t (kW)
C_T	Rated capacity of the distribution transformer (kVA)
U(t)	Transformer utilization index at time block t (%)
MAPE	Mean Absolute Percentage Error (%)
MAE	Mean Absolute Error (kWh or MW)
ERR	Energy Recovery Ratio — recovered vs. lost energy (%)
E_del	Total energy delivered (TWh)
E_rec	Recovered energy (TWh)

Introduction

The Middle East is undergoing a major transformation of its power sector, driven by grid modernization, renewable energy integration, and growing customer expectations. To address rising electricity demand and the increasing complexity of power distribution networks, utilities require intelligent, data-driven solutions that enhance operational efficiency, improve grid resilience, and support a more reliable and sustainable energy future.

Traditional grid operations—heavily reliant on manual processes—are increasingly inadequate. Losses, delayed response to anomalies, and reactive upgrades erode both financial performance and service quality. To address this, utilities are turning to artificial intelligence (AI) and advanced analytics as the cornerstone of smart grid transformation.

This paper proposes an AI-powered analytics and grid intelligence framework that builds a self-learning ecosystem across multiple utility functions, ensuring operational efficiency, loss reduction, and superior customer engagement.

Methodology

The methodology adopted in this paper follows a structured, end-to-end approach to building an AI-powered Utility intelligence ecosystem. It begins with source-of-supply identification to establish accurate meter-to-transformer mapping, forming the foundation for all subsequent analytics. Non-intrusive load disaggregation then provides appliance-level insights, which feed into anomaly detection frameworks to safeguard revenue and reduce losses. Transformer load monitoring and forecasting enable proactive capacity planning, while continuous AI feedback loops refine performance over time. Finally, GenAI-driven decision tools ensure that actionable intelligence is easily ac cessible to planners, engineers, and customer service teams through intuitive, interactive interfaces.

A. Source of Supply Identification

Accurate Source-of-Supply (SoS) identification—mapping consumer meters (CMs) to their corresponding distribution transformers (DTs)—is fundamental for grid intelligence [7]. It establishes the backbone for transformer load monitoring, anomaly detection, and loss analysis. Incorrect mapping leads to distorted load profiles, unreliable forecasting, and inefficiencies in outage management. The methodology combines spatial analysis with electrical signal correlation in a multi-stage screening process:

The SoS methodology adopted combines spa tial analysis with electrical signal correlation to create a robust, multi-stage screening process:

1 · Spatial Proximity

DT GIS coordinates superimposed on meter lusters; initial associations via minimum Euclidean distance.

2 · Reference Meter

The meter closest to the DT is chosen as the Reference Meter (RM), serving as the correlation baseline.

3 · Voltage Correlation

30-day voltage & harmonic profiles compared to RM; Pearson coefficient > 0.8 confirms association.

This process is iterated for all DT–CM pairs, in cluding unmapped cases, with optional expan sion to second-nearest clusters when needed.

Advanced ML clustering algorithms are applied to group CMs, followed by superimposing transformer coordinates on these clusters. An initial mapping is then created by calculating the minimum Euclidean distance between DTs and the closest meters.

To refine this mapping, a reference meter is selected within each cluster, and voltage cor relation analysis is performed over 1–2 days of time-series data. By computing the Pearson correlation coefficient, only meters with correlation above a set threshold (typically >0.8) are confirmed as correctly associated with the transformer. This two-stage process—spatial clustering followed by electrical correlation— significantly improves accuracy.

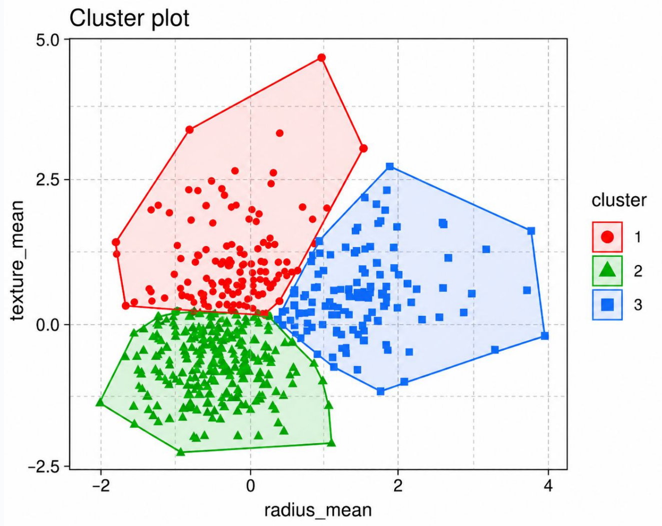

Figure 1: Initial Clusters sample based on spatial proximity

Illustrations of sample cases studies of sample Meter mapping. Figures 2 and 3 illustrate suc cessful mapping cases where the voltage pro file of a consumer meter closely aligns with that of the identified Reference Meter (RM). The high degree of similarity in the time-series voltage patterns confirms that these meters are correctly associated with the same distri bution transformer. Such correlation-based validation strengthens the confidence in Source-of-Supply identification, particularly in cases where GIS data alone may not be sufficient.

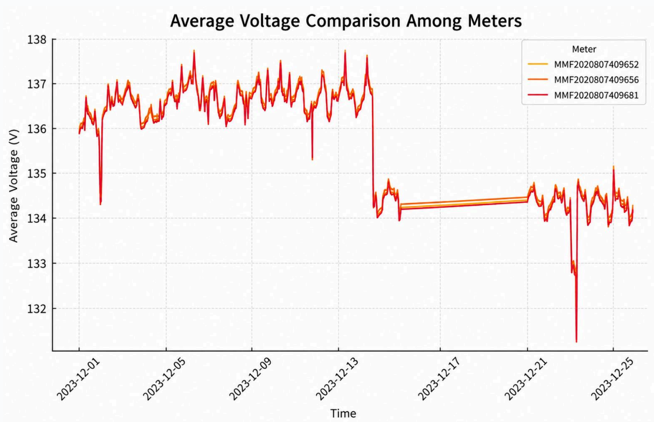

Figure 2. Average voltage comparison — consumer meter profile matching the reference meter, confirming correct transformer association.

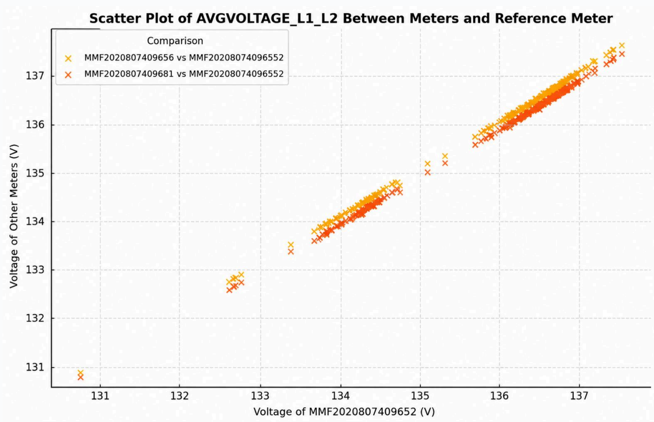

Figure 3. Correlation plot — tightly clustered points along the diagonal indicate high voltage correlation (matching case).

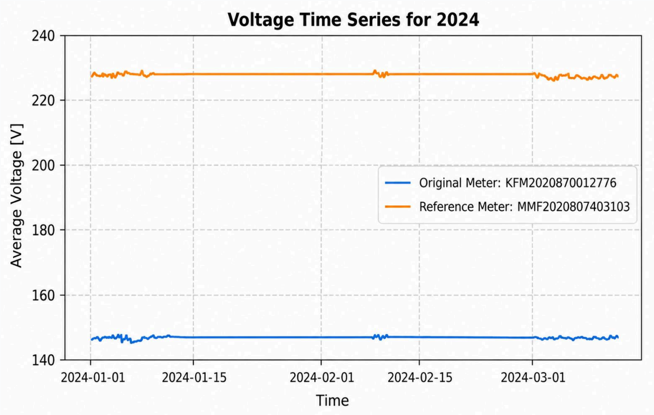

Figure 4. Average voltage comparison — meter profile diverging from the reference meter, flagging a likely mis-mapping.

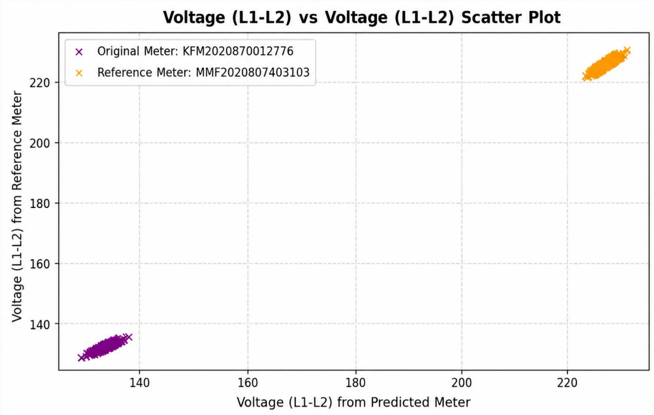

Figure 5. Correlation plot — dispersed points reveal weak correlation, indicating a meter supplied by an adjacent transformer.

The ML-driven workflow also addresses in complete data by iteratively remapping un mapped meters using the second nearest clus ter. Outputs include three key data frames: mapped DT–CM pairs, unmapped records, and missing values.

In contrast, Figures 4 and 5 highlight scenarios where the voltage profile of a meter diverges significantly from the RM profile. These differ ences, often seen as dispersed or inconsistent patterns, indicate that the meter is unlikely to belong to the same transformer supply. Such mismatches typically arise from GIS inaccura cies, cross-phase connections, or the pres ence of meters supplied by adjacent trans formers. Identifying and flagging these anoma lies is critical, as it allows utilities to prioritize corrective validation in the field and refine the accuracy of automated SoS mapping.

In a pilot study, this methodology has achieved ~80% mapping accuracy when validated against ground-truth data. By embedding SoS identification within the AI-powered grid eco system, utilities ensure that subsequent analyt ics, whether for anomaly detection or trans former forecasting, are rooted in clean, vali dated topology data, ultimately strengthening decision-making across the value chain.

B. Non-Intrusive Load Disaggregation (NILD)

Instead of deploying intrusive sub-meters, NILD leverages AI-driven pattern recognition to identify the operational signatures of key appli ances [2], [3]. Signature-based true load dis aggregation algorithms leverage energy con sumption patterns, weather conditions, and dwelling characteristics to accurately uncover real customer behavior based on daily appli ance usage. Each appliance emits a distinct energy signature, which our AI continuously detects and tracks across all homes in real time- enabling precise, appliance-level insights into household energy consumption.

The evaluation is grounded in a direct compari son between the model-predicted load profiles and the actual ground truth measurements ob tained from appliance-level sensors installed in few houses. The analysis focuses on five criti cal residential appliances- including air condi tioners, refrigerators, washing machines, water heaters, and pool pumps due to their signifi cant contribution to total energy consumption and behavioral variability. Model performance is assessed using key metrics such as Mean Absolute Error (MAE), F1 Score, Accuracy, and Energy Recovery Ratio (ERR), offering a multi dimensional view of disaggregation accuracy [2]. This enables a robust understanding of not only the raw prediction accuracy but also the model's ability to capture operational patterns and appliance switching behaviors. The NILD framework employs a hybrid Transformer-CNN architecture optimized for appliance-level load identification. The pipeline consists of:

- **Data Preprocessing:** Noise reduction, missing value handling, and smoothing to isolate usable patterns.
- **Feature Fusion:** Combination of handcrafted signal descriptors (voltage/current waveforms, harmonics) with deep spatiotemporal features.
- **CNN with Attention:** A convolutional backbone enhanced with Efficient Channel Attention (ECA) modules to prioritize informative channels.
- **Transformer Layer:** Self-attention captures long-term dependencies in power signals, learning appliance "languages" such as compressor cycles or binary on/off operations.
- **Decoding Layer:** Reconstructs appliance-specific load profiles from abstract feature space, aligning them with the original aggregate signal Model Refinement Load Disaggregation.

This design ensures both fine-grained recogni tion of short events (e.g., switching) and accu rate modelling of long-duration appliances (e.g., AC units). This is where the model learns the "language" of your appliances- mapping how they behave in the household energy system.

Below mentioned are sample

Table 1 · Individual Appliance Signatures

Category	Typical Appliances	Power Range	Usage Cycles / Patterns
HVAC	Air Conditioners, Heaters, Fans	0.5 – 4 kW	2–3 cycles daily, peaks during cooling hours (12–6 PM)
Cooking	Refrigerators, Ovens, Microwaves, Cooktops, Dishwashers	0.1 – 5 kW	Peaks during meal preparation (7–9 AM, 6–8 PM)
Cleaning	Washing Machines, Dryers, Irons, Vacuum Cleaners	0.5 – 5 kW	Single or batch operations, often morning/evening
Entertainment	TVs, Consoles, Computers, Printers	0.05 – 0.08 kW	Longer cycles during leisure hours (6–11 PM)
Others	Lighting, Pool Pumps, Small Appliances, Always-On Loads	0.005 – 3 kW	Highly irregular; forms baseline consumption throughout the day

Figure 6. Individual Appliance Power Consumption Signatures

Non-Intrusive Load Disaggregation Insights and Applications

Appliance-Level Insights:

NILD enables utilities to decompose aggregate consumption into appliance-level contributions, providing a much clearer view of end-use behaviour. The disaggregation results consistently highlight:

- HVAC dominance during peak cooling periods, where air conditioning systems represent the largest share of residential demand.
- Cooking appliance surges concentrated around mealtimes, typically during morning and evening hours.
- Cleaning appliance cycles (washing machines, dryers, vacuum cleaners) clustered in morning and late-evening usage slots.
- Entertainment loads such as televisions, consoles, and home electronics that peak during leisure hours, particularly in the evenings.
- Always-on baseline loads contributed by lighting, standby electronics, and small appliances, which create a constant background demand.
- These insights allow utilities to move beyond aggregate consumption statistics and understand the behavioural drivers of household energy use.

Role in Demand Side Management (DSM)

By linking appliance-level consumption to grid stress, NILD becomes a powerful enabler of DSM strategies:

- Identification of stress drivers: Pinpointing the specific appliances responsible for peak transformer loading.
- Load-shifting recommendations: Encouraging consumers to shift energy-intensive activities, such as AC cooling, to off-peak periods.
- Fault detection and preventive maintenance: Detecting abnormal appliance behavior (e.g., malfunctioning refrigerators) that may indicate inefficiency or tampering.
- Personalized energy insights: Delivering customized household energy reports that highlight high-consumption appliances and suggest actionable efficiency measures.

In this way, NILD provides the analytical bridge between consumer behaviour and grid stability, making DSM programs more targeted and effective.

Strategic Benefits for Utilities and Customers

The deployment of NILD within Saudi Arabia's electricity sector delivers multiple layers of value:

- Cost-Efficiency: Eliminates the need for intrusive sub metering by using data from existing smart meters.
- Scalability: Capable of being deployed across millions of customers with minimal incremental investment.
- Energy Savings: Identifies inefficiencies and opportunities for behavioural changes that reduce household and system-level consumption.
- Customer Empowerment: Provides households with transparency into their appliance-level usage, improving awareness and engagement.

C. Anomaly Detection & Revenue Protection

Non-technical losses represent a significant economic challenge for utilities globally, with developing countries experiencing losses ranging from 15-40% of total generation. Traditional detection methods rely on statistical analysis of consumption patterns, customer complaint investigation, and periodic field audits, proving inadequate for sophisticated fraud schemes and large-scale theft operations.

Machine learning approaches for anomaly detection leverage consumption pattern analysis, customer profiling, and network topology information for enhanced fraud identification. Clustering algorithms including k-means, DBSCAN, and hierarchical clustering effectively segment customers based on consumption behaviour [14], enabling identification of outlier patterns.

Supervised learning approaches using labelled fraud datasets achieve high accuracy but suffer from class imbalance problems [15] and limited adaptability to evolving fraud techniques. Unsupervised approaches, particularly isolation forests and one-class SVMs, provide robust anomaly detection [16] without requiring labelled training data.

Deep learning architectures for anomaly detection include autoencoders for reconstruction-based anomaly scoring, LSTM networks for temporal anomaly detection, and generative adversarial networks for sophisticated fraud pattern identification. Graph neural networks represent the latest advancement, incorporating network topology and customer relationships for topology-aware anomaly detection [18].

D. Transformer Load Monitoring (TLM)

By aggregating smart meter data at the transformer level, utilities can continuously monitor utilization. Machine learning models such as Light GBM for short-term (daily) forecasts and SARIMAX for long-term (monthly) forecasts provide early warnings of potential overloads [8]. Transformer load monitoring is built on the principle of aggregating smart meter data to accurately reconstruct distribution transformer (DT) load profiles. Since no direct sensors are installed at DTs, customer smart meter (SM) readings are consolidated to derive the total load connected to each transformer. Each SM records consumption at 48 half-hourly intervals per day and provides a daily aggregated energy value, ensuring both fine temporal resolution and long-term energy accounting.

The aggregation process begins by mapping all meters to their respective transformers. For each time block, the transformer load is estimated as the sum of all customer loads. The transformer utilization index is then calculated as the ratio of aggregated load to rated capacity, expressed as a percentage. This provides continuous visibility into operating conditions, from underloaded transformers (<50%) to those nearing or exceeding overload thresholds (>90%). Data preprocessing techniques are employed to address real-world issues such as missing values, outliers, and temporal misalignment, ensuring that the aggregated dataset is reliable for downstream analysis.

To anticipate future loading, this methodology employs a hybrid forecasting framework that combines machine learning and statistical models. For short-term (daily) forecasts, a Light Gradient Boosting Model (Light GBM) is used to predict peak demand and total daily consumption up to 30 days ahead. The model incorporates historical load curves, weather inputs, and temporal features such as weekdays and holidays. For medium-term (monthly) forecasts, a SARIMAX model captures seasonal demand patterns and broader consumption trends, producing accurate projections of monthly peaks and total energy. Model accuracy is assessed using Mean Absolute Percentage Error (MAPE), and retraining cycles are triggered whenever prediction errors exceed acceptable thresholds. This adaptive learning process ensures that the models remain aligned with evolving demand conditions.

The complete workflow—from Smart Meter data aggregation to forecasting and anomaly detection—can be integrated into Utility's analytics platform. Outputs include transformer-level utilization dashboards, predictive load curves, and anomaly alerts. These insights directly support operational decision-making by highlighting overloaded assets, enabling load redistribution, and helps in grid expansion planning.

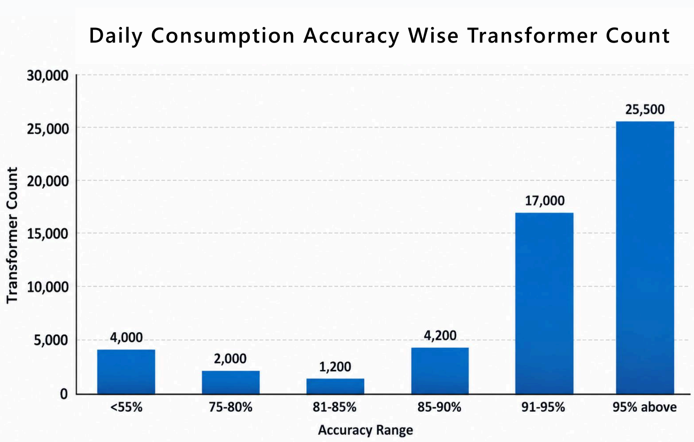

Figure 7. Summary of Accuracy achieved for Transformer Daily Consumption

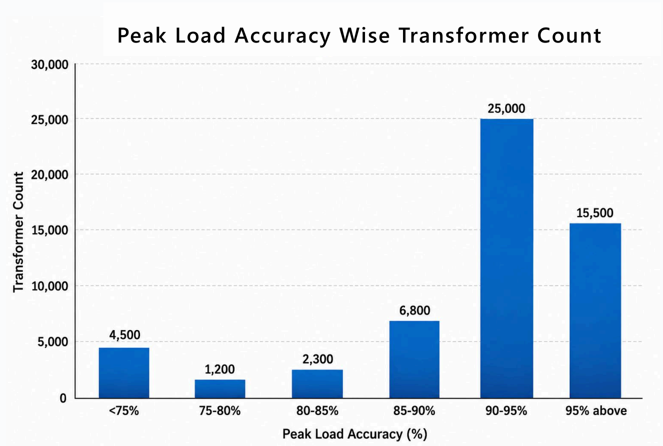

Figure 8. Summary of Accuracy achieved for Transformer Peak Load

As covered in figure 7 above Most transformers achieve high daily consumption accuracy (90% and above), with the majority exceeding 95% accuracy. Very few transformers are in the low-accuracy categories (<90%). This suggests strong reliability and data quality for many monitored transformers. Figure 8: Summary of Accuracy achieved for Transformer Peak Load

As covered in figure 8, Most transformers achieve high peak load accuracy (above 90%), with the highest concentration in the 90–95% range. Compared to daily consumption accuracy (previous chart), slightly fewer transformers reach the 95%+ bracket, but overall reliability remains high, with the bulk of transformers performing well above 90%.

E. AI Feedback Loops

The system is designed as a living ecosystem. Forecast errors and anomaly detection accuracy feed back into model retraining pipelines. Reinforcement learning ensures continuous performance improvement across load disaggregation, anomaly detection, and forecasting.

F. GenAI Decision Tools

Generative AI applications—integrated into mobile apps and dashboards—allow planners, engineers, and customer service representatives to query system intelligence in natural language. For example, asking “Which Transformer in Riyadh face overload risk in July?” produces interactive dashboards with drill-down capability.

AI-Powered Smart Meter Analytics: Creating Strategic Utility Advantage

The various use cases described above collectively form an integrated ecosystem of smart meter data analytics, where synergies across applications drive operational excellence within utilities.

Source-of-Supply (SoS) identification provides the foundational layer by accurately mapping meters to their respective distribution transformers [7]. This ensures visibility into the true flow of power across the network and explains why certain transformers appear overloaded while others remain underutilized due to incomplete or incorrect meter mapping.

These insights directly feed into the Transformer Load Monitoring (TLM) application, which continuously tracks transformer utilization [8]. The system highlights transformers operating below capacity as well as those approaching critical overload conditions. Such intelligence enables utilities to plan network reinforcement and expansion proactively, reducing the risk of unplanned outages and strengthening customer service reliability.

Building on this, Non-Intrusive Load Disaggregation (NILD) adds further depth by identifying which end-use appliances contribute most to peak transformer loads [2],[3]. By linking appliance-level insights to transformer stress, utilities can design targeted Demand Side Management (DSM) strategies that address the root causes of overloading rather than treating only the symptoms.

Finally, GenAI-powered insights operate as a unifying horizontal layer across all smart meter analytics modules. By synthesizing outputs from SoS, TLM, and NILD, the GenAI layer not only explains the drivers of peak loads but also generates actionable recommendations for planners, operators, and policy makers. This holistic, AI-driven framework transforms raw smart meter data into operational intelligence, supporting both near-term grid reliability and long-term strategic planning.

Financial Impact Assessment

The potential financial benefits of AI-enabled smart meter analytics can be quantified using a bottom-up, tariff-based approach. This method calculates the incremental kilowatt-hours (kWh) recovered, or saved through operational efficiencies, and converts the recovered energy into monetary terms using the utility's per-unit tariff. Table 2 below provides estimated benefits of the above-mentioned use cases. All savings percentages are derived from global utility benchmarks (DOE, MIT Sloan, NEMA, ACEEE, MDPI) and represent indicative values.

Table 2 · Use-case-wise estimated benefits

Use Case	Impact Pathway	Estimated Benefit	Ref
Source-of-Supply (SoS) Identification	Provides the foundation for accurate meter-to-transformer mapping, enabling precise anomaly detection, load monitoring, and loss dashboards.	Indirect contributor to anomaly detection and TLM benefits	[7]
Transformer Load Monitoring (TLM)	Improves transformer utilization by avoiding overload-related technical losses.	Recovered energy ~0.2% of annual delivered energy	[8]
Anomaly Detection (ML-Based Theft & Loss Reduction)	Identifies unbilled energy from theft, bypasses, and abnormal load profiles.	Recovered energy ~0.5% of annual delivered energy	[14]–[18]

Further, Financial benefits can be calculated based on these formulas:

$$\text{Revenue Recovery} = \text{Recovered Energy (TWh)} \times 10^9 \text{ kWh} \times \text{Tariff (SAR/kWh)}$$

Future Enhancements

While the current framework demonstrates clear value in loss reduction, load forecasting, and anomaly detection, the path ahead offers even greater opportunities to transform utility operations. The following directions outline the next evolution of AI-powered grid intelligence in Saudi Arabia.

A Integration with BESS and EV Load Forecasting

The rapid adoption of Battery Energy Storage Systems (BESS) and electric vehicles (EVs) in Saudi Arabia will introduce new dynamics into demand profiles and system flexibility. AI-driven forecasting models will be enhanced to:

- Predict EV charging demand patterns at both residential and fleet levels, differentiating between home charging, public stations, and bus depots.
- Forecast BESS charge–discharge cycles to optimize grid balancing, peak shaving, and renewable energy integration.
- Enable co-optimization of EVs and BESS as grid assets, helping utilities treat them as distributed energy resources rather than passive loads.

By combining EV load forecasts with BESS operational models, utilities can minimize transformer stress, extend asset life, and enhance grid reliability.

B Expanded GenAI-Driven Customer Engagement Platforms

Beyond internal operations, utilities must transform customer engagement. Generative AI (GenAI) applications will evolve into powerful, customer-facing tools that:

- Deliver personalized energy insights (e.g., "your EV charging added 15% to your monthly bill; consider shifting charging to off-peak hours").
- Provide intelligent self-service assistants, capable of resolving most customer queries without human intervention.
- Enable multilingual, natural language interfaces, bridging diverse customer bases across Saudi Arabia.
- Offer interactive mobile platforms that not only display consumption data but also simulate "what-if" scenarios for energy savings and billing.

This will improve customer satisfaction, reduce call-Centre costs, and position the utility as a customer-centric digital utility.

In summary, the future of AI in Saudi Arabia's electricity sector lies not only in refining current modules but in expanding intelligence to new frontiers—EVs, BESS, and GenAI-enabled customer engagement. These advancements will reinforce the grid's resilience, unlock new business models, and strengthen the Kingdom's leadership in smart grid innovation under Vision 2030.

Conclusion

AI-powered analytics and grid intelligence offer Saudi utilities a transformative pathway toward a self-learning, continuously improving ecosystem. By unifying meter-to-transformer mapping, non-intrusive load disaggregation, anomaly detection, and advanced forecasting under a single AI framework, utilities can generate reliable insights that scale across the entire grid. The result is not only operational efficiency but also measurable financial gains through revenue protection, deferred capital expenditure, reduced operational costs, and improved service reliability.

Beyond financial metrics, this transformation strengthens the grid's ability to adapt to new challenges. Accurate topology data ensures a solid foundation for decision-making, while AI-driven forecasting prepares utilities for demand surges and renewable variability. Anomaly detection enables near real-time revenue protection, and GenAI-driven decision tools empower both field engineers and executives with actionable intelligence. Collectively, these capabilities shift utilities from reactive problem-solving to proactive grid management.

Most importantly, this AI-driven transformation is directly aligned with the ambitions of Saudi Vision 2030. By embedding intelligence at every layer of the electricity value chain, the Kingdom positions itself as a global leader in smart grid innovation, setting benchmarks for operational resilience, sustainability, and customer-centric services. The adoption of AI-powered grid intelligence not only ensures greater energy security and reliability but also enhances customer trust by delivering accurate billing, faster response times, and personalized engagement.

Looking ahead, this holistic approach lays the groundwork for integrating emerging technologies such as BESS optimization, EV load management, and advanced DERMS. As these elements mature, the self-learning ecosystem will evolve into a dynamic, adaptive grid, capable of handling growing demand, integrating renewable energy at scale, and supporting new digital business models.

In essence, AI-powered analytics represent more than a technology upgrade—they mark the beginning of a new era where utilities evolve into data-driven, customer-focused, and globally competitive organizations, ensuring that the Kingdom's electricity sector not only meets present challenges but thrives in the decades ahead.

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