Grid Modernization · Vision 2030

Transformer Load Monitoring and Forecast

A smart meter–based approach to transformer utilization monitoring, load forecasting, and proactive asset management for power distribution networks in the Middle East.

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Abstract—This paper presents the implementation of a smart monitoring system for distribution transformer loads across Middle East power distribution networks. Unlike conventional approaches, where sensors are physically installed at transformers, this initiative derives transformer loading indirectly through the aggregation of smart meter data. Each consumer meter records half-hourly load values across 48-time blocks per day, in addition to providing daily energy consumption totals. These data are consolidated at the transformer level to estimate utilization, monitor operational conditions, and forecast future load behavior

The forecasting framework employs a hybrid approach: Light Gradient Boosting Models (Light GBM) for daily load and consumption prediction, and SARIMAX for monthly peak demand forecasting. Model performance is evaluated using Mean Absolute Percentage Error (MAPE), with adaptive retraining to ensure sustained accuracy. The Riyadh case study demonstrates how this approach improves transformer utilization, predicts overload conditions, and enables proactive asset management. Beyond technical accuracy, the system delivers measurable operational, economic, and customer benefits, supporting Saudi Arabia's Vision 2030 grid modernization objectives.

Nomenclature

Below mentioned are the important abbreviations covered in this paper.

kWh	Kilo Watt hour (Consumption)	**kVA**	Kilo Volt Ampere (Apparent Load)
ME	Middle East	**SCADA**	Supervisory Control and Data Acquisition
EV(s)	Electric Vehicle(s)	**Load Aggregation**	Summation of meter level load at transformer level, for the meter mapped to that transformer.
L(t)	Load Profile of a Transformer, covers load for 48-time blocks on that Transformer	**M(L)**	Meter level Load profile i.e., Apparent Load (kVA) for 48-time blocks in a day.
Max T(L)	Maximum load on a transformer in a day, captures the maximum load amongst the load for 48-time blocks.	**Transformer Utilization Index**	This index captures the maximum utilization of a transformer based on the maximum load on that transformer and the rated capacity of the transformer
Light GBM	Light Gradient Boosting Model	**SARIMAX**	Seasonal Autoregressive Integrated Moving Average with Exogenous Factors.
MAPE	Mean Absolute Percentage Error	**GIS**	Geographic Information System

Introduction

Distribution transformers are critical elements in electricity networks, serving as the final link between medium-voltage feeders and low-voltage consumers. Their health and performance directly affect power quality, reliability, and system efficiency. However, monitoring these assets presents significant challenges, particularly in rapidly expanding cities like Riyadh. Historically, utilities relied on periodic inspections, oil sampling, or SCADA-based alarms, all of which are reactive and limited in coverage.

The widespread deployment of smart meters has created a new data-rich environment. Each meter captures fine-grained consumption information, offering an opportunity to infer transformer loads indirectly. By aggregating these data streams, utilities can monitor transformer utilization, identify overloads, and detect anomalies without installing dedicated sensors at every transformer. This approach aligns with global smart grid trends toward data-driven asset management.

This paper details the implementation of transformer load monitoring using smart meter aggregation across power distribution networks in the Middle East. It outlines the data processing methodology, forecasting framework, and anomaly detection techniques, and presents a case study from a major urban load center in the region. In addition, the paper explores the broader benefits for distribution utilities, including improved operational efficiency, economic advantages, enhanced planning capabilities, integration with renewable energy and electric vehicles (EVs), and alignment with regulatory and customer service objectives.

Methodology

The effectiveness of the transformer load monitoring framework depends on the integration of diverse yet complementary datasets. Smart meter readings provide granular, consumer-level consumption profiles, while weather parameters enrich the forecasting models by accounting for demand drivers such as temperature-sensitive loads. Together, these inputs enable accurate aggregation of load at the transformer level and support reliable forecasting of demand patterns. By relying on existing digital infrastructure rather than deploying additional field sensors, the approach ensures scalability, cost efficiency, and practical implementation for utilities.

A. Data Sources

The monitoring system relies on two primary inputs:

Smart meter data

Each consumer provides half-hourly load profile i.e., apparent power (kVA) across 48-time blocks per day, as well as daily aggregated consumption (in kWh). By mapping consumers to their parent transformers, these data streams are summed to estimate transformer-level load curves.

Weather data (used for Load Forecasting)

External variables such as temperature and humidity are incorporated in capturing demand drivers, particularly the cooling load in Riyadh during summer months.

This data-driven approach eliminates the need for transformer-mounted sensors, reducing cost and complexity while leveraging existing infrastructure.

B. Load Aggregation and Utilization Index

The Total Transformer load at a time is defined as

Load on Transformer T(L) $= \sum_{i=1}^{n} M_i$

Transformer Utilization Index $\dfrac{\text{Max}\,(T(L))}{C(T)}$

i. Mi= Meter level Load 24 hours load profile in kVA
ii. T(L)= Summation of the meter level load at Transformer level.
iii. Max (T(L)) = Gives the Peak demand at Transformer level, after aggregating the meter level load at that transformer level.
iv. C(T)= Rated Capacity of Transformer

This metric enables continuous assessment of underloading, optimal operation, or overload risk.

Table 1: Sample data explaining aggregation of Meter level load profile (kVA) at Transformer level

Time Block	Hours	Meter 1 (kVA)	Meter 2 (kVA)	Meter 3 (kVA)	Meter 4 (kVA)	Meter 5 (kVA)	Transformer Level Load Aggregation (kVA)
1	00:00-00:30	37.5	37.8	26.2	5.2	9.0	115.7
2	00:30-01:00	39.9	45.3	20.6	5.3	4.5	112.2
3	01:00-01:30	43.3	37.7	17.2	4.8	4.8	104.4
4	01:30-02:00	37.7	37.2	18.2	6.1	11.8	116.6
5	02:00-02:30	37.6	37.0	13.5	7.2	10.9	106.3
6	02:30-03:00	43.3	33.8	11.4	4.2	16.2	103.2
7	03:00-03:30	39.9	26.4	14.6	6.9	17.4	108.6
8	03:30-04:00	34.9	26.9	8.4	6.4	17.6	99.2
9	04:00-04:30	37.1	31.0	0.0	5.3	17.1	88.3
10	04:30-05:00	32.4	27.4	7.9	2.0	17.1	91.5
11	05:00-05:30	30.7	24.9	4.9	3.8	23.4	89.4
12	05:30-06:00	31.2	20.4	4.6	9.1	30.4	95.2
13	06:00-06:30	22.2	19.9	6.4	4.4	30.5	92.4
14	06:30-07:00	20.7	16.0	4.5	10.1	27.4	80.2
15	07:00-07:30	22.4	12.3	5.8	13.6	34.6	87.0
16	07:30-08:00	18.7	15.7	0.0	13.1	37.3	88.5
17	08:00-08:30	20.9	8.7	3.5	12.8	34.4	78.1
18	08:30-09:00	14.7	5.4	11.5	13.8	39.6	91.2
19	09:00-09:30	10.9	12.1	8.4	19.4	40.4	95.0
20	09:30-10:00	18.5	11.6	4.8	20.2	37.0	84.5
21	10:00-10:30	11.1	0.4	8.2	19.9	43.0	90.0
22	10:30-11:00	10.4	9.1	10.2	24.6	44.0	99.0
23	11:00-11:30	4.0	0.0	15.3	25.4	45.8	96.9
24	11:30-12:00	5.8	11.9	15.6	28.8	45.4	105.7
25	12:00-12:30	7.0	5.2	16.9	26.9	35.9	90.7
26	12:30-13:00	2.2	13.3	20.9	26.1	36.5	103.8
27	13:00-13:30	6.8	9.5	24.3	26.8	40.5	103.3
28	13:30-14:00	3.5	15.1	24.0	23.0	39.0	107.9
29	14:00-14:30	4.8	10.6	24.9	28.3	37.2	104.5
30	14:30-15:00	4.2	17.2	27.1	28.0	47.2	124.3
31	15:00-15:30	13.1	27.0	31.0	20.88	33.3	113.7
32	15:30-16:00	8.0	32.9	31.4	22.38	33.1	132.0
33	16:00-16:30	5.9	30.8	34.9	21.17	30.1	136.1
34	16:30-17:00	13.6	32.2	30.1	21.00	26.6	117.8
35	17:00-17:30	8.6	29.5	32.0	20.96	20.7	121.4
36	17:30-18:00	15.2	30.3	37.1	20.99	22.2	124.2
37	18:00-18:30	10.1	38.7	32.6	21.05	14.4	116.9
38	18:30-19:00	14.3	40.5	39.1	20.87	14.2	131.0
39	19:00-19:30	21.5	44.0	38.8	20.46	11.3	121.8
40	19:30-20:00	25.5	45.8	38.8	20.08	11.5	135.4

As covered in Table 1: Sample data explaining aggregation of Meter level load profile at Transformer level, the maximum Apparent Power (Max T(L)) on this sample Transformers occurs at 41 Time Block 20:00-20:30 hours, equivalent to 137.6 kVA.

This Maximum Load of Transformer in kVA is divided by the rated capacity of the transformer. Assuming rated capacity of Transformer as 500kVA. Transformer Utilization Index becomes 34%.

C. *Forecasting Methodology*

To anticipate transformer loading, a dual model forecasting framework was adopted (see Figure X).

Daily horizon — **Light GBM**

A Light Gradient Boosting Model (Light GBM) predicts daily peaks and consumption up to 30 days in advance. The model captures nonlinear interactions between consumer behavior, weather, and historical load.

Monthly horizon — **SARIMAX**

A Seasonal Auto Regressive Integrated Moving Average with Exogenous variables (SARIMAX) model forecasts monthly peaks and energy consumption for up to three months, capturing longer-term seasonal trends.

Both models are retrained periodically, with performance assessed using Mean Absolute Percentage Error (MAPE). If accuracy degrades, models are updated with new data to maintain reliability.

Data Ingestion
Smart meter + weather
→
Aggregation
Meter → transformer
→
Model Training
LightGBM · SARIMAX
→
Forecast Output
Daily & monthly peaks
→
MAPE Evaluation
Accuracy assessment

Accuracy degraded → adaptive retraining with new data

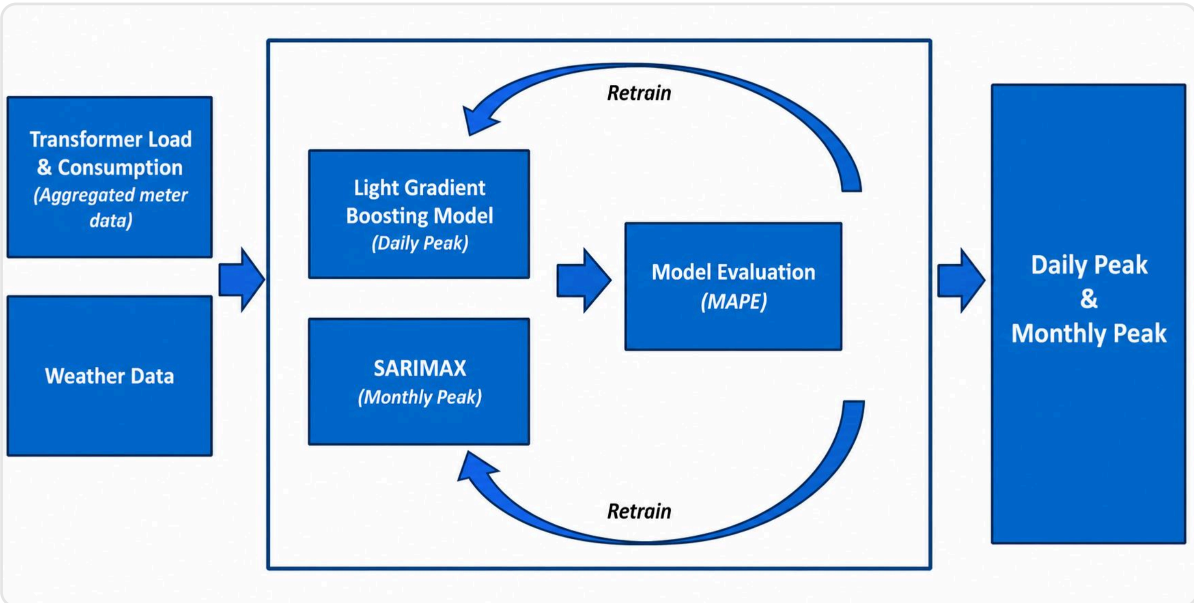

Figure 1: Forecasting Model Evaluation cycle flowchart.

Case Study:

The utility case study demonstrates the practical application of the proposed monitoring and forecasting framework in one of Middle East's most critical load center. By analyzing real transformers and weather datasets, the study highlights the distinctive demand patterns that characterize the city's energy use. The results provide insights into both operational challenges, such as peak management, and strategic opportunities for optimizing transformer utilization. This evidence-based approach showcases the system's ability to deliver actionable intelligence for grid operators in dynamic urban environments.

A. Study Region and Dataset

This sample case study focusses on Utility, the largest urban load center in Middle East's. Data was collected for several hundred transformers, covering multiple months of operation.

The user can analyse the overloaded transformer count from the home page of the Transformer load monitoring.

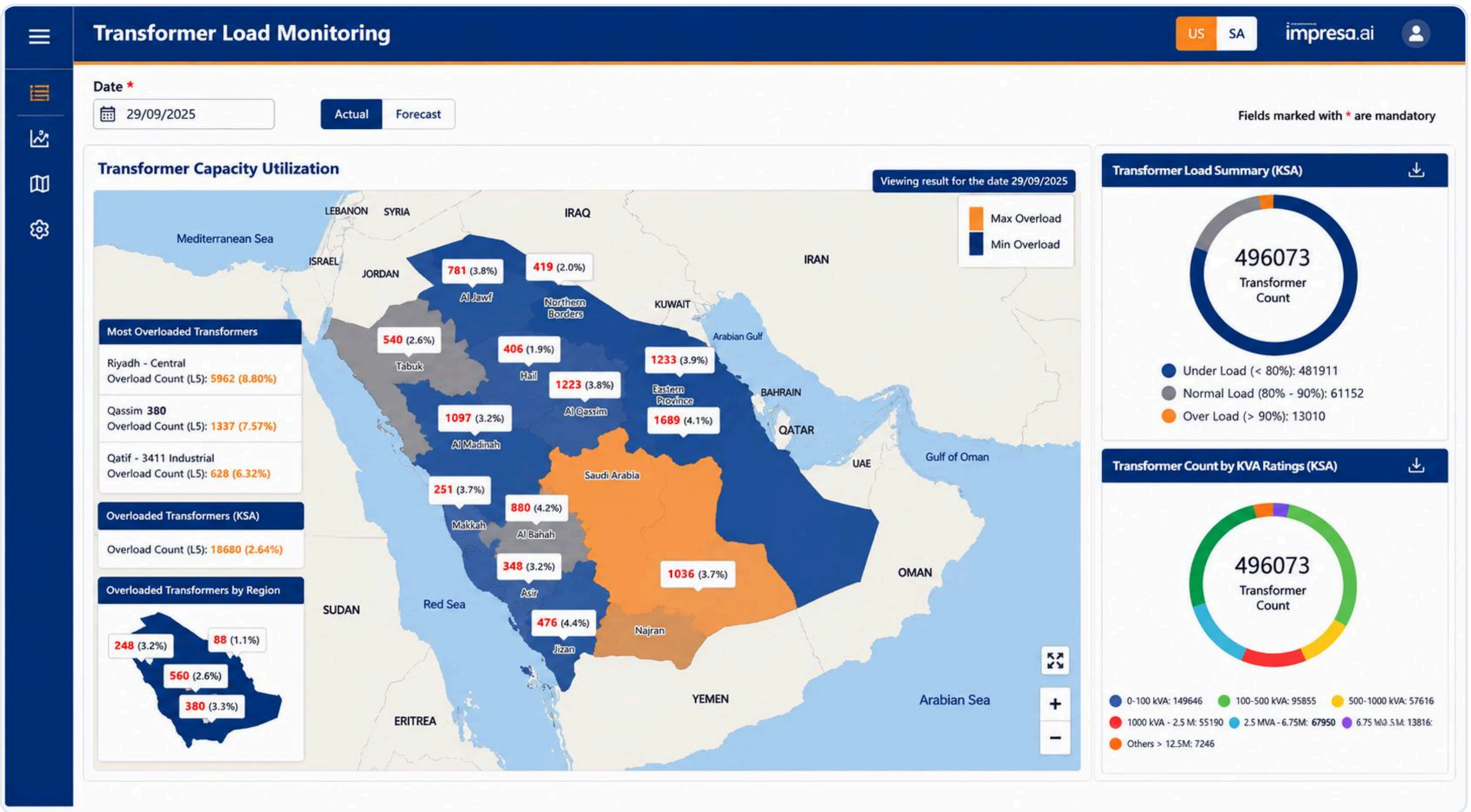

Figure 2: Transformer Load Monitoring Home Page

Transformer Load Monitoring Home Page provides a nationwide Transformer Capacity Utilization dashboard for Saudi Arabia. The heat map highlights overloaded transformers by region, with additional drill-down options available by clicking directly on the KSA map to explore department- and office-level details. A smooth toggle button allows users to seamlessly switch between actual and forecast utilization views, supporting both real-time monitoring and forward looking planning. Accompanying summary charts display the overall transformer count, categorized by utilization bands (<30%, 30–80%, >80%), as well as the distribution by kVA ratings. This integrated view enables planners to pinpoint hotspots, anticipate future stress, and optimize network investment strategies across the Kingdom.

B. Transformer Utilization Analysis

The interface provides a GIS-based view of thousands of transformers, color-coded by utilization levels, enabling quick identification of stressed or underutilized assets. Summary panels highlight overall transformer counts and capacity distribution, while interactive filters allow drill-down by region, department, or office. This visualization bridges operational data with decision-making, offering planners an intuitive tool for Load monitoring.

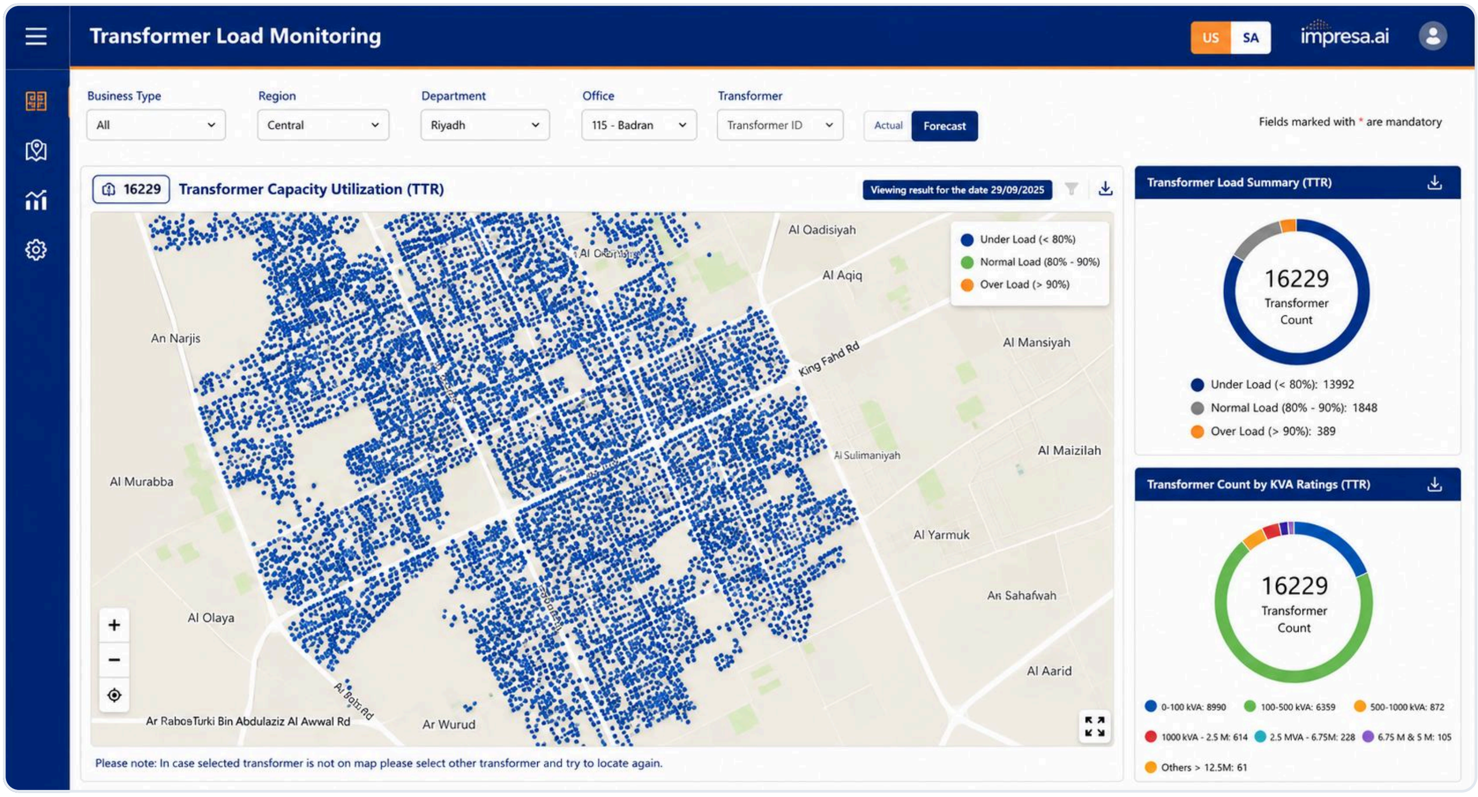

Figure 3: Heat Map of Transformer utilization for Transformers in office code 1110

C. Forecasting Results

Light GBM achieved daily forecast errors below % (MAPE), while SARIMAX captured monthly seasonal trends with acceptable accuracy. Forecasts of daily peaks allowed operators to schedule proactive switching, while monthly predictions supported capacity planning.

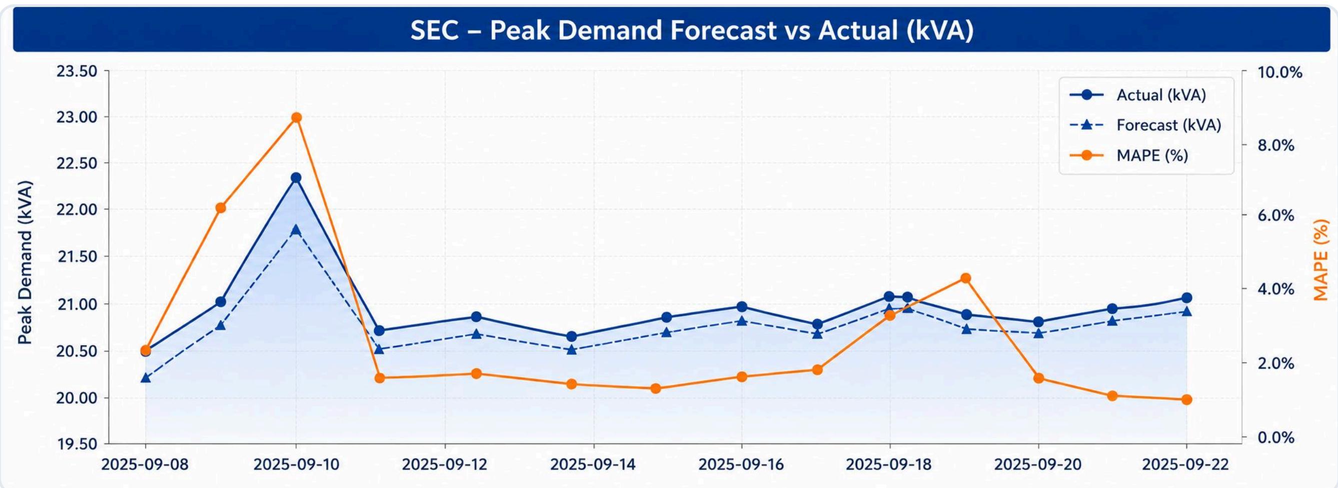

Figure 4: Actual vs predicted load for a sample Riyadh transformer.

Table 2: Sample data for Actual and Forecast Peak demand for Transformer 4100-CDS-084538

Datetime	Actual (kVA)	Forecast (kVA)	MAPE
08-09-2025	21.12	20.88	1.15
09-09-2025	21.12	22.38	5.95
10-09-2025	21.20	21.17	0.15
11-09-2025	21.12	21.00	0.56
12-09-2025	21.12	20.96	0.76
13-09-2025	21.12	20.99	0.64
14-09-2025	21.20	21.05	0.71
15-09-2025	21.12	20.87	1.17
16-09-2025	21.20	20.46	3.50
17-09-2025	21.12	20.08	4.92
18-09-2025	21.12	20.60	2.45
19-09-2025	21.12	20.97	0.69
20-09-2025	21.12	20.98	0.67
21-09-2025	21.12	21.01	0.51
22-09-2025	21.20	21.14	0.28

As covered in figure 4 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.

As covered in figure 5, 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%.

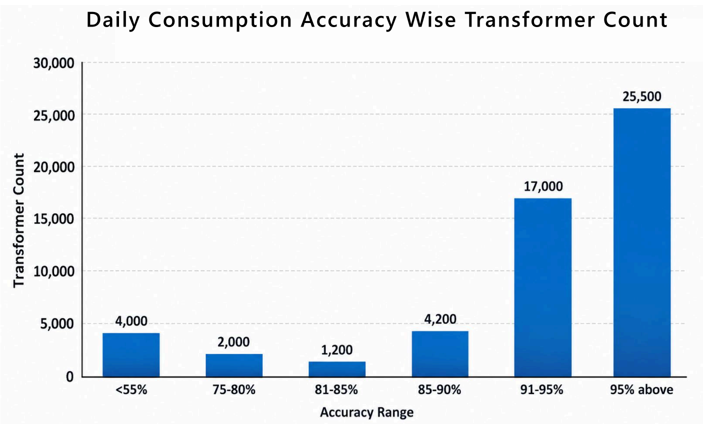

Figure 5: Summary of Accuracy achieved for Transformer Daily Consumption

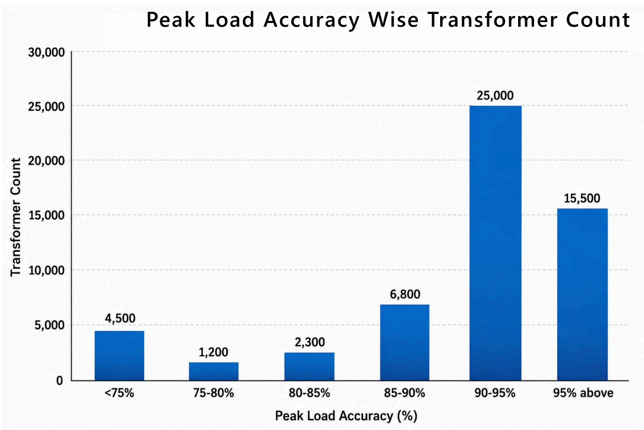

Figure 6: Summary of Accuracy achieved for Transformer Peak Load

Utility Impact

A. Operational Efficiency

The monitoring system enables utilities to shift from reactive to proactive operations by providing real-time visibility into transformer loading and potential stress conditions. This improves reliability, reduces outages, optimizes maintenance activities, and minimizes the need for manual field inspections.

B. *Economic Benefits and Asset Management*

Proactive monitoring extends transformer lifespan by preventing thermal and electrical stress. The financial impact includes:

Deferred replacements
transformers no longer fail prematurely.

Avoided investments
capacity upgrades are postponed by optimizing load distribution.

Reduced losses
balancing loads across units reduces technical losses.

C. Planning and Network Design

Forecasting data provides a robust basis for network planning. Planners can identify where new transformers are required, right-size equipment for new developments, and reconfigure feeders to balance load. Integration with GIS enables spatial visualization of hotspots.

D. Support for Renewables and EVs

With the growing adoption of rooftop solar and electric vehicles (EVs), transformer loading is becoming increasingly dynamic and variable. Continuous monitoring helps ensure that transformers have sufficient capacity to accommodate distributed energy resources (DERs) while maintaining reliable operation. In addition, load forecasting supports the assessment of EV charging demand and diversity, enabling utilities across the Middle East to plan effectively for future electricity demand growth.

E. Regulatory and Policy Alignment

The system supports compliance with reliability standards such as SAIDI and SAIFI by reducing outages and improving grid performance. It also enhances reporting accuracy and supports the modernization goals of power distribution utilities across the Middle East.

F. Customer Reliability and Satisfaction

Improved monitoring directly benefits customers by reducing outages, shortening restoration times, and ensuring more consistent power quality. This enhances the reliability of power distribution networks, strengthens customer trust, and contributes to higher customer satisfaction.

Future Releases under development

While the current implementation of transformer load monitoring and forecasting delivers significant operational and planning benefits, additional capabilities are under development to further enhance the solution's value for power distribution utilities in the Middle East. Two key enhancements are envisioned:

A. Network Planning Assistance Tool

This module extends the monitoring framework into proactive network planning. By integrating utilization indices, load curves, and GIS-based spatial data, the tool will recommend the most suitable transformer for new meter connections. The objective is to ensure that new loads are connected only to transformers with sufficient spare capacity, thereby avoiding unplanned overloading. In practice, planners will be able to simulate multiple connection scenarios, assess future utilization trends, and balance load growth across the distribution network. This functionality reduces the risk of premature transformer failure, supports efficient asset deployment, and aligns with long-term capacity planning objectives.

B. Transformer Ageing and Health Assessment

Another planned enhancement focuses on predictive ageing analysis, enabling utilities to transition from transformer load monitoring to comprehensive asset health management. This module integrates four critical dimensions to provide a holistic assessment of transformer condition and remaining service life:

Loading Status

Continuous tracking of transformer utilization relative to rated capacity. Persistent overloading or frequent operation near capacity accelerates insulation deterioration and shortens asset life.

Total Harmonic Distortion (THD)

Identifies additional thermal stress from harmonic currents, a growing concern with the rise of non-linear loads such as EV chargers and rooftop solar inverters.

Age Since Installation

Historical asset records will be used to correlate load history with expected end-of-life cycles.

Phase Imbalance

By analysing asymmetry in phase loading, the system will quantify additional wear-and-tear that accelerates ageing.

The ageing model will generate transformer health scores and risk categories, enabling utilities to prioritize asset replacement, schedule maintenance, and take corrective actions before failures occur. Combined with load forecasting, it provides a comprehensive view of current utilization and long-term asset health, supporting more effective maintenance and investment planning.

Conclusion

This study demonstrates the successful deployment of transformer load monitoring in the Middle East using smart meter aggregation. By leveraging existing infrastructure, the system provides accurate transformer utilization insights, reliable load forecasts, and early warnings of stress conditions. The Riyadh case study confirms operational improvements, including reduced outage risk, extended asset life, and deferred investment. Forecasting models (Light GBM for daily, SARIMAX for monthly) achieved high accuracy, enabling better planning and resource allocation.

Beyond its technical capabilities, the system delivers significant benefits for distribution utilities, including improved operational efficiency, cost savings, enhanced planning and asset management, greater readiness for renewable energy and electric vehicle (EV) integration, stronger regulatory compliance, and improved customer satisfaction. Collectively, these benefits support the transition toward a more digital, resilient, and future-ready power distribution grid across the Middle East.

Looking ahead, future enhancements will expand the platform with a Network Planning Assistance Tool for optimizing new customer connections and a Transformer Ageing and Health Assessment module for predictive maintenance. Together, these capabilities will transform the solution into a comprehensive planning and asset management platform for power distribution networks across the Middle East.

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