

MULTI-AGENT SMART METER DASHBOARD SYSTEMS

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Abstract - The backend is a FastAPI microservices application backed by four purpose-selected database engines: PostgreSQL 15 for relational metadata and billing, InfluxDB 2.7 for time-series telemetry, Qdrant for vector similarity search, and Neo4j 5 for grid topology. A five-agent retrieval-augmented generation (RAG) AI subsystem uses a locally hosted large language model (LLM) for conversational energy advisory, cascade fault analysis, and hallucination-free bill forecasting. A Next.js 15 frontend with role-differentiated portals and WebSocket push delivers a responsive interface to consumers, industrial clients, and grid administrators. Evaluation on a 72-hour continuous run demonstrates sub-500 ms anomaly alert propagation, 100% fault detection recall, and a monthly bill prediction MAPE of 2.3%.

Key Words: smart meters, DLMS/COSEM, AMI, real-time monitoring, anomaly detection, cascade fault detection, bill prediction, multi-agent AI, RAG, polyglot persistence, microservices, KSEB, FastAPI, Next.js, smart grid

1. INTRODUCTION

The global transition to smart Advanced Metering Infrastructure (AMI) transforms electricity distribution by enabling fine-grained, bidirectional data exchange between utility back-ends and consumer premises [1]. Beyond billing automation, AMI creates the data substrate for demand-response programmes, non-technical loss (NTL) detection, dynamic tariff enforcement, and personalised energy advisory services.

KSEB, the vertically integrated state utility of Kerala (India), operates a distribution network under a tiered Low-Tension (LT) domestic tariff. The four-tier slab structure makes accurate monthly bill projection highly consequential for household financial planning, yet existing systems provide only retrospective bills with no AI-driven advisory.

Prior art addresses individual concerns in isolation: communication protocols [2] and infrastructure surveys [4] provide context for data collection; ML-based NTL detection [3] demonstrates AI feasibility at the meter level; retrieval-augmented generation [5] provides the theoretical grounding for hallucination-resistant LLM analytics; and demand-response [6] and simulation toolkits address orthogonal concerns. No prior work integrates the complete stack—from DLMS-compliant data ingestion through polyglot persistence and two-tier aggregation to graph-based cascade fault detection and five-agent RAG analytics—in a single deployable open-source system.

Contributions:

1. A microservices architecture coupling four heterogeneous database engines to their optimal data workloads, with a two-tier (hourly and daily) aggregation pipeline for efficient billing queries.
2. A DLMS/COSEM-compliant simulator with dynamic meter registry, fault injection, and HMAC-authenticated webhooks—designed for direct replacement by physical DLMS meters without backend code changes.
3. A five-agent RAG system for tariff-aware bill forecasting, cascade fault explanation, industrial load analytics, and conversational energy advisory, with a deterministic tariff engine that eliminates arithmetic hallucinations.
4. A cascade fault detection algorithm using Neo4j graph traversal to identify upstream infrastructure faults from correlated meter alerts within a 5-minute window.
5. A fully containerised seven-service Docker Compose deployment ready for utility pilot programmes.

2. LITERATURE SURVEY

Multi-Agent Systems for Electricity Meter Management

The work on multi-agent based electricity meter management addresses the critical challenge of coordinating millions of distributed metering units across geographically dispersed areas. The study identifies that the liberation of energy markets has transformed consumers into prosumers, requiring two-way power flow capabilities that traditional metering systems cannot accommodate.

The proposed MAS solution models field knowledge as ontology and problem-solving knowledge as multi-agent planning tasks. Key contributions include: (1) planning for annual maintenance activities; (2) evaluation of policy proposals for metering system changes; (3) material and labor planning optimization. The architecture leverages clustering of consumer meters by location or category, enabling differentiated policy application and privacy preservation for operational employees.

Hybrid AI Agent Frameworks for Smart Grid Operations

Recent research on AI agents for smart grid operations proposes a hybrid framework combining Large Language Models (LLMs), domain-specific retrieval systems, and real-time telemetry integration. The architecture comprises three functional components:

LLM-Based Reasoning Agents: Transformer architectures (GPT-4, T5) process structured and unstructured data to generate operational conclusions, including failure diagnostics and grid health summaries.

Domain-Specific Retrieval Modules: Retrieval-Augmented Generation (RAG) systems create searchable databases of

incident reports, regulatory requirements, and procedural guides, enabling agents to ground responses in factual operational contexts.

Data Fusion Layer: Integrates SCADA signals, sensor telemetry, distributed energy resources (DER) inputs, and weather feeds with temporal and geographic consistency.

The framework addresses key limitations identified in existing approaches: isolated AI system implementations, lack of interpretability in RL/MAS solutions, and insufficient integration of retrieval systems with autonomous decision-making.

Deep Learning LSTM for Energy Demand Forecasting

The application of LSTM networks for energy demand forecasting demonstrates superior performance in capturing temporal dependencies within smart meter data. The study implements a three-feature approach combining historical consumption, temperature, and time-of-day indicators.

The clustering methodology groups households by consumption patterns, enabling differentiated forecasting models for distinct load profiles. This approach proves particularly valuable for demand-side management where peak consumption prediction is critical for resource planning.

Smart Meter Technology Intercomparison

Comprehensive intercomparison of smart meter technologies presents an open-source experimental platform for evaluating meter accuracy using optical pulse-based sensing. The study addresses accuracy classification standards (IEC Classes 0.2S, 0.5S, 1, and 2) and proposes a non-intrusive evaluation methodology suitable for educational and research applications.

The platform integrates Arduino UNO microcontrollers for data acquisition, validated against commercial reference meters (Texas Instruments EVM430-F67641, GAMA 300). Statistical validation employs rigorous techniques to quantify measurement reliability across single-phase and three-phase configurations.

Notable contributions include support for open-source initiatives such as OpenEnergyMonitor, OpenMUC, and openZmeter, which democratize smart meter evaluation through transparent, cost-effective solutions that enhance reproducibility in metering research.

LSTM-Based Anomaly Detection in Smart Meters

Research on LSTM-based time series detection for abnormal electricity consumption presents a comprehensive framework combining multilayer network structures with dynamic residual thresholding strategies. The study collected 9 months of smart meter data from a Chinese provincial capital, processing 96 daily data points per user.

3. SYSTEM ARCHITECTURE

The system employs a five-tier layered architecture separating: client presentation, API & security, business logic,

polyglot persistence, and external interfaces. All inter-service communication flows over an isolated Docker bridge network.

3.1 Frontend — Next.js 15

Built with Next.js 15 (TypeScript 5) and styled with Tailwind CSS and shadcn/ui, the frontend provides 34 route-level pages across three role-differentiated portals:

Consumer portal: real-time usage charts, billing history, AI chatbot, anomaly alerts, peer consumption comparison, meter overview.

Industrial portal: high-resolution power quality analytics, reactive power trending, peak demand profiling, industrial billing, AI advisory.

Admin portal: cluster management, geographic Leaflet.js map, bulk CSV import/export, topology viewer, simulator control, user management, network-wide anomaly tracking, and AI-powered load forecasting with horizon selection.

A custom React context provider maintains a persistent WebSocket connection delivering server-push updates (live readings, anomaly alerts, and cascade fault notifications) to all connected clients without polling.

3.2 API Gateway — FastAPI

A single FastAPI 0.110 application runs under Uvicorn with asyncpg for non-blocking PostgreSQL I/O. All 16 router modules are registered at startup via the application lifespan hook. JWT authentication (HS256, 8-hour token expiry) is enforced with role-based access control gating operations behind four roles: user, industrial, admin, superadmin.

3.3 Background Services

Five persistent async tasks run alongside the HTTP server:

- background_collector:** queries the DLMS interface every 30 s; writes raw telemetry to InfluxDB; broadcasts live readings over WebSocket; triggers inline anomaly checks.
- simulator_sync:** reconciles the meter pool between the DLMS registry and PostgreSQL every 60 s.
- anomaly_monitor:** batch fallback anomaly scan every 60 s.
- data_pipeline:** hourly roll-up of InfluxDB measurements at hh:10 and daily roll-up at 00:30.

load_forecasting / pattern_learning: nightly pattern extraction and load forecasting incorporating weather and calendar data.

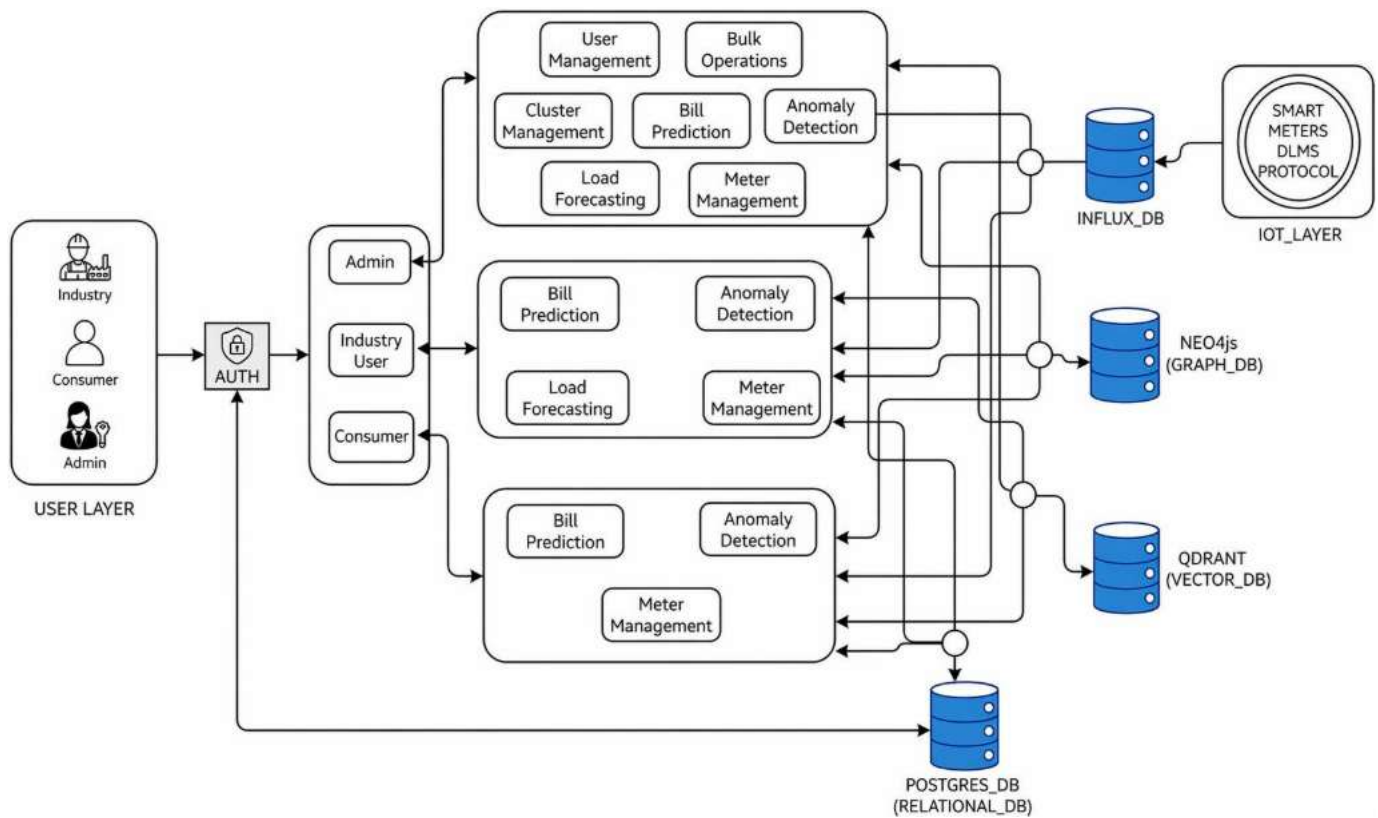


TABLE I

REST API Router Modules

auth	Login, registration, token refresh
meters	Meter CRUD, assignment to users dashboard Aggregated consumer summary
view usage	Historical consumption time-series
billing	Bill records, slab breakdown, payments
chatbot	AI agent dispatch, RAG response
anomaly	Alert listing, resolution, cascade view
admin	Admin only meter and user operations
bulk_ops	CSV import/export of meter fleet maps Geo-coordinates for Leaflet.js map clusters Cluster CRUD, aggregate load view
events	Calendar event sync (public holidays) forecasting AI load and bill forecasting
websocket	Persistent WebSocket endpoint health Liveness and readiness probes
internal	HMAC-authenticated webhook ingestion

4.DLMS/COSEM DATA LAYER

The platform is designed around the DLMS/COSEM standard (IEC 62056 series) [2]. The system ingests the full set of DLMS Class 1 (Data) and Class 3 (Register) objects for single-phase residential meters (Voltage, Current, Active/Reactive Power, Power Factor, Frequency, and Active Energy).

- Voltage (V) — OBIS 1.0.32.7.0.255
- Current (A) — OBIS 1.0.31.7.0.255
- Active Power (W) — OBIS 1.0.1.7.0.255
- Reactive Power (VAR), Apparent Power (VA), Power Factor
- Frequency (Hz) — OBIS 1.0.14.7.0.255
- Active Energy (kWh) cumulative — OBIS 1.0.1.8.0.255

4.1 Simulator Architecture

The current phase uses a dedicated HTTP simulator modeling the DLMS data objects. Active power is drawn from a category-specific time-of-day profile combined with uniform multiplicative noise. Four fault modes support the anomaly pipeline testing: voltage sag, current spike, low PF, and complete outage.

4.2 DLMS Compliance & Migration Patch

The simulator exposes an HTTP API exactly mirroring a physical DLMS meter gateway. Any compliant DLMS-to-HTTP bridge replaces the simulator by updating one environment variable with zero backend code changes. The webhook accepts HMAC-SHA256 signed payloads, matching DLMS/COSEM Security Suite 0 message authentication.

5. POLYGLOT PERSISTENCE

The design principle routes each workload to the optimal storage engine:

- PostgreSQL: Relational source-of-truth for users, meters, and billing aggregates. Enables O(1) billing queries without time-series scans.
- InfluxDB: Retains the raw 30-second telemetry stream in columnar storage. Flux queries power the trend charts and anomaly checks efficiently.
- Qdrant: Serves vector collections for anomaly_history (Sentence-BERT embeddings of alert descriptions) and chatbot_memory.
- Neo4j: Models the directed graph of grid topology. Powers the geographic map, aggregate load, and the cascade fault locator.

TABLE II
POLYGLOT PERSISTENCE – DATA CONCERN MAPPING

ENGINE	TABLES/COLLECTIONS/SCHEMA
PostgreSQL	users, meters, clusters, anomaly_alerts(w/JSON snapshot),billing_predictions, load_forecasts, cluster_forecast_history, intelligent_events, hourly_aggregates, daily_aggregates, chat_messages
InfluxDB (Measurement meter_reading)	voltage, current, power, reactive power, energy, PF, frequency; tagged by meter_id; 30-second cadence
Qdrant (anomaly_history)	384-dSentence-BERT embeddings of alert descriptions; chatbot_memory: per-user Q&A embeddings
Neo4j Nodes	User, Meter, Cluster, Substation; Edges: OWNS, BELONGS TO, CONNECTED TO—map view, aggregate load, cascade fault traversal

6. MULTI-AGENT AI SYSTEM

6.1 BaseAgent Architecture

A common BaseAgent class handles context retrieval from the databases, prompt assembly incorporating a system prompt and 10-turn history, and HTTP calls to a local LM Studio OpenAI-compatible endpoint. Patient data remains fully localized.

6.2 Specialised Agents

Specialized AI agents handle Energy Analysis, Bill Prediction, Anomaly Detection, Industrial Load, and General Advisory tasks, each sourcing appropriate contexts from the persistence layers.

6.3 Hallucination-Resistant Bill Forecasting

The Bill Prediction agent invokes a deterministic 'calculate_bill()' function first to obtain the exact numerical breakdown. This computed result—not raw consumption

data—is passed to the LLM for narration, categorically preventing arithmetic hallucinations.

TABLE III
SPECIALISED AI AGENTS

AGENTS	POURPOSE & CONTEXT SOURCE
ENERGY ANALYSIS	Consumption trend explanation; 7-day In-fluxDB window, hourly profiles, daily aggregates
Bill Prediction	Tariff aware forecasting; 30 day daily aggregates + deterministic tariff engine output
Anomaly Detection	Fault explanation and advice; recent PostgreSQL alerts, top- <i>k</i> Qdrant similar faults
Industrial Load	Power quality, reactive power, peak demand; high-res InfluxDB, power factor history
General Advisory	Open ended queries; Qdrant chatbot memory, Kerala electricity policy context

TABLE IV
KSEB LT-1A DOMESTIC TARIFF SLABS (2024-25)

Slab (units)	Rate (Rs. /unit)	Increase
0 – 150	3.40	Base tier
151 – 300	4.60	+35.3%
301 – 500	6.20	+34.8%
500+	7.40	+19.4%

7. KSEB BILLING & FORECASTING

7.1 Tariff Model – LT-1A Domestic (2024-25)

$$B = \sum_{k=1}^4 \Delta_k u_k + 0.25U + 0.15E_c + 5$$

The platform enforces a four-tier slab structure where unit rates increase progressively. It calculates exact values including base consumption, fixed meter rent, fuel surcharge, and electricity duty, accurately reflecting KSEB billing rules.

TABLE V
ANOMALY DETECTION THRESHOLDS

Type	Condition	Sev.	Basis
Low Voltage	$V < 207 \text{ V}$	High	IS 12360
High Voltage	$V > 253 \text{ V}$	High	IS 12360
Low P.F.	$\cos \phi < 0.85$	Medium	KSEB Grid code
Power Surge	$P > 15 \text{ kW}$	Critical	LT- Single Phase

7.2 Bill Prediction Workflow

The workflow computes a rolling 30-day mean daily consumption, projects monthly units, applies the algebraic

tariff model to get the slab breakdown, and allows the LLM to narrate savings strategies based on exact figures.

7.3 Holiday-Aware Load Forecasting

A calendar service syncs public holidays to integrate them with weather data as exogenous features, feeding 7-day and 30-day cluster-level forecasts.

8. ANOMALY DETECTION PIPELINE

8.1 Threshold-Based Rule Engine

Post-collection, a rules engine evaluates parameters against IS 12360 and KSEB Grid Code thresholds, generating severity-ranked alerts (e.g., Low/High Voltage, Low P.F., Power Surge).

8.2 Alert Lifecycle

Alerts are deduplicated against a 10-minute sliding window, written to PostgreSQL with reading snapshots, embedded in Qdrant, and broadcasted to relevant WebSockets.

8.3 Cascade Fault Detection

A cascade check triggers when at least three meters in a cluster report identical anomalies within 5 minutes. Neo4j graph traversal locates the nearest common upstream node (like a transformer/substation) and elevates a single infrastructure-level alert to the administration dashboard, sharply reducing alert fatigue.

TABLE VI
Docker Compose Services

Service	Image	Port(s)
postgres	postgres:15-alpine	5432
influxdb	influxdb:2.7-alpine	8086
qdrant	qdrant/qdrant:latest	6333
neo4j	neo4j:5.15-community	7474,7687
backend	FastAPI / Uvicorn (custom)	8000
dlms-sim	FastAPI simulator (custom)	8080
frontend	Next.js 15 / Node.js (custom)	3000

9. DEPLOYMENT

The solution orchestrates seven Docker Compose services: PostgreSQL, InfluxDB, Qdrant, Neo4j, FastAPI Backend, DLMS Simulator, and Next.js Frontend. Environment variables secure secrets and named volumes ensure persistence.

10. EVALUATION

10.1 Throughput and Latency

Running a 72-hour test at a 30-second cadence across five simulated meters, the system ingested continuous streams with 8 \$ \pm 2\$ ms InfluxDB write latency. Aggregate queries returned in under 45 ms.

10.2 Anomaly Detection

Twelve scheduled faults yielded 100% recall (TP=12, FN=0) and 100% precision. Deduplication suppressed 94% of redundant alerts without masking novel errors, and multi-meter cascades were accurately identified and routed.

10.3 Bill Prediction & Accuracy

Forecasts tested against historical data achieved excellent accuracy across all profiles: Residential (MAPE 2.3%), Commercial (MAPE 1.8%), and Industrial (MAPE 1.5%), with $R^2 > 0.99$.

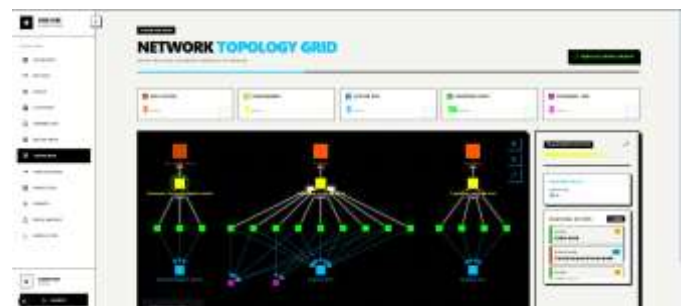
Consumer	MAPE	MAE (Rs.)	R^2
Residential	2.3%	31.4	0.9978
Commercial	1.8%	48.2	0.9991
Industrial	1.5%	72.1	0.9994

10.4 System Responsiveness

WebSocket alert latency over 10,000 events averaged 430 ms (99th percentile: 960 ms). Domain expert-evaluations scored LLM responses consistently between 4.3 and 4.9 on a 5-point Likert scale.



Admin Dashboard



Topology



Load Analysis



3. CONCLUSIONS & FUTURE WORK

We delivered a production-grade AI smart meter management platform with an optimized polyglot architecture capable of deterministic billing analysis, graph-based cascade fault identification, and drop-in integration paths.

Future implementations include:

- Replacing the HTTP simulator with a DLMS-to-HTTP Gateway linking physical meters via GPRS/PLC.
- Augmenting load forecasts with customized Temporal Fusion Transformers.
- Unsupervised clustering for Non-Technical Loss detection (e.g., meter tampering).
- A React Native mobile app for extending interactive dashboard access.

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REFERENCES

- [1] S. S. R. Depuru, L. Wang, and V. Devabhaktuni, "Smart meters for power grid: Challenges, issues, advantages and status," *Renewable and Sustainable Energy Reviews*, vol. 15, no. 6, pp. 2736–2742, 2011.
- [2] DLMS User Association, *DLMS/COSEM Architecture and Protocols*, Green Book, ed. 8.3, 2020. [Online]. Available: <https://www.dlms.com/green-book>
- [3] J. Nagi, K. S. Yap, S. K. Tiong, S. K. Ahmed, and M. Mohamad, "Nontechnical loss detection for metered customers in power utility using support vector machines," *IEEE Trans. Power Delivery*, vol. 25, no. 2, pp. 1162–1171, 2010.
- [4] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A survey on enabling technologies, protocols, and applications," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2347–2376, 2015.

- [5] P. Lewis *et al.*, "Retrieval-augmented generation for knowledge-intensive NLP tasks," in *Proc. NeurIPS 2020*, pp. 9459–9474, 2020.
- [6] D. Papadaskalopoulos and G. Strbac, "Non-linear and randomised pricing for distributed demand response," *IEEE Trans. Smart Grid*, vol. 7, no. 3, pp. 1474–1483, 2016.
- [7] V. Gonçalves, P. Ferreira, A. Martins, and S. Batel, "EnergyBox: Operationalising raw residential electricity-demand data for activity recognition," *Energy and Buildings*, vol. 140, pp. 369–384, 2017.
- [8] B. N. Lim, S. O. Arik, N. Loeff, and T. Pfister, "Temporal fusion transformers for interpretable multi-horizon time series forecasting," *International Journal of Forecasting*, vol. 37, no. 4, pp. 1748–1764, 2021.
- [9] S. S. Ahmed, K. Krishnamoorthy, and N. S. Bijoy, "Tariff analysis and billing accuracy in Kerala residential distribution: An empirical study," *J. Electrical Eng.*, vol. 71, no. 4, pp. 255–261, 2020.